Psychological Review
2005, Vol. 112, No. 4, 777–813

0033-295X/05/$12.00 DOI: 10.1037/0033-295X.112.4.777

SWIFT: A Dynamical Model of Saccade Generation During Reading

Ralf Engbert, Antje Nuthmann, Eike M. Richter, and Reinhold Kliegl
University of Potsdam

Mathematical models have become an important tool for understanding the control of eye movements during reading. Main goals of the development of the SWIFT model (R. Engbert, A. Longtin, & R. Kliegl, 2002) were to investigate the possibility of spatially distributed processing and to implement a general mechanism for all types of eye movements observed in reading experiments. The authors present an advanced version of SWIFT that integrates properties of the oculomotor system and effects of word recognition to explain many of the experimental phenomena faced in reading research. They propose new procedures for the estimation of model parameters and for the test of the model's performance. They also present a mathematical analysis of the dynamics of the SWIFT model. Finally, within this framework, they present an analysis of the transition from parallel to serial processing.

In modern society, reading is a central skill, which demonstrates how efficiently a range of different cognitive processes (e.g., visual information processing, word recognition, attention, oculomotor control) can work together to perform a complex everyday task. Consequently, a full account of how we read is among the crucial problems of cognitive research. Here, we focus on the fact that eye movements in reading represent an important example for a coupled cognitive–motor system. Therefore, a detailed analysis of the interface between high-level cognition (word recognition) and eye-movement control (saccade generation) is essential to contribute to our knowledge of reading.

The measurement, analysis, and modeling of eye movements is one of the most powerful approaches to studying the way visual information is (a) processed by the human mind and (b) used to guide our actions (Findlay & Gilchrist, 2003). Measurements of fixation durations on words or on regions of text are central for investigating cognitive processes underlying reading (Liversedge & Findlay, 2000; Rayner, 1998). Therefore, it is of central importance to develop a detailed understanding of how the experimental observables are related to the underlying cognitive systems.

Over the last decades, there has been a considerable increase of knowledge about eye movements and visual information processing (e.g., Hyönä, Radach, & Deubel, 2003; Radach, Kennedy, & Rayner, 2004; Rayner, 1998). The question of how the contributing cognitive subsystems for a specific task such as reading are coordinated is a research problem representative of questions that we believe cannot be investigated without fully quantitative mathematical models. Although it is still possible to investigate aspects of eye-movement control (e.g., word skipping or programming of refixations) in a nonmathematical way, a fully quantitative approach in which most of the experimental phenomena are integrated is necessary to test the interaction of different theoretical assumptions (e.g., the potential impact of a mechanism for word skipping on refixation behavior). In perspective, computational models can be approximated with analytical means to check the numerically obtained results and to derive the foundations of a rigorous theory of eye-movement control during reading (e.g., Engbert & Kliegl, 2003a).

Our main goal in this article is to propose a mathematical model for the control of eye movements during reading that is both psychologically and neurophysiologically plausible and that accounts for most of the known experimental findings. The model presented here is an advanced and substantially extended version of the SWIFT[1] model proposed earlier (Engbert, Longtin, & Kliegl, 2002). The model is motivated by many different experimental results, which we discuss in detail. The model incorporates neurophysiological properties of the oculomotor system. Furthermore, the SWIFT model is compatible with a general framework of the generation of saccades developed by Findlay and Walker (1999) and shares concepts with the dynamic field theory of movement preparation by Erlhagen and Schöner (2002). As our cognitive systems have never been under evolutionary pressure to optimize reading abilities (i.e., there has been no special adaptation of humans for reading), plausible models of eye movements in reading must have the potential for generalization to task manipulations (e.g., reading with a scotoma) and nonreading tasks (e.g., visual search). We discuss the issue of generalizability later in this article.

The model that we develop here is a minimal model, which is related to two aspects of model design. First, the model is based on only a few core principles. This is a challenging problem, because even when reading relatively simple sentences, patterns of eye movements turn out to be very complex. As an example, we observe several different types of saccades including word skipping (no fixation on the skipped word), refixations (more than one fixation on the same word), and even interword regressions (backward saccades landing on a previously fixated region of text). The

Ralf Engbert, Antje Nuthmann, Eike M. Richter, and Reinhold Kliegl, Department of Psychology, University of Potsdam, Potsdam, Germany.

This work was supported by Deutsche Forschungsgemeinschaft Grants KL 955/3 and KL 955/6. We thank Erik D. Reichle and Francoise Vitu-Thibault for their valuable comments on the manuscript.

Correspondence concerning this article should be addressed to Ralf Engbert, Department of Psychology, University of Potsdam, P.O. Box 60 15 53, 14415 Potsdam, Germany. E-mail: engbert@rz.uni-potsdam.de

[1] (Autonomous) **S**accade-Generation **W**ith **I**nhibition by **F**oveal **T**argets.

formulation of separate assumptions for these different types of eye movements would violate the principle of minimal modeling. Therefore, we aim at a general mechanism underlying all types of saccades—the fundamental principle of our model. Second, the core assumptions of our model are idealizations, which will be formulated mathematically in a parsimonious way (i.e., with as few parameters as possible). Minimal modeling is also related to generalizability, because, with an increasing number of assumptions specific to reading, the model would be more and more inflexible to explain eye movements in different tasks. How we control eye movements in visual search should be in agreement with the main control principles guiding the eyes during reading.

A theoretical framework for the dynamics of movement preparation with a very general claim is the *dynamic field theory* (Erlhagen & Schöner, 2002). In this theory, a field of activation—the mathematical term for a function of space *and* time—is spatially distributed over a number of potential movement targets. Using concepts from the theory of nonlinear dynamical systems, the dynamic field theory proposes laws governing the temporal evolution of such activation fields. In the dynamic field theory, there is continuous cross talk between different cognitive subsystems (e.g., memory system, perceptual input, movement planning). This continuous interaction of cognition and motor control makes the theory highly relevant to eye-movement control during reading, as the selection of words as saccade targets must be performed on the basis of partial knowledge, because saccade latency requires an early start of the next saccade program during fixation. Thus, a temporally continuous interaction between processes of word recognition and saccade generation is essential in a plausible model of eye-movement control during reading. Although we do not refer to the explicit formalism proposed by Erlhagen and Schöner (2002), we use the concept of an activation field already developed in the first version of the SWIFT model (Engbert et al., 2002). Note, however, that the assumption of an activation field already has strong implications. A theory built around the core assumption of a dynamically changing activation field necessarily involves spatially distributed processing. In reading, words are the elementary targets for the saccadic system. To build up an activation field, several words must be activated in parallel. This parallel processing, however, is not necessarily related to word recognition, but could be limited to early stages of word processing. We discuss this important aspect of our model later and derive different types of parallel processing of words.

The first version of our model of eye-movement control in reading[2] (Engbert et al., 2002) was developed as a viable alternative to the models based on sequential shifts of attention, a principle that motivated the development of the currently most advanced model, E-Z Reader (Reichle, Pollatsek, Fisher, & Rayner, 1998; Reichle, Rayner, & Pollatsek, 1999, 2003; see also Engbert & Kliegl, 2001). Because of the success of the E-Z Reader model, which is based on strictly sequential processing, some researchers speculated that an alternative model based on parallel processing of words could not perform similarly well. For example, Starr and Rayner (2001, p. 162) concluded that “such a model seems rather complicated and would be difficult to implement in a computational model. Thus, a challenge for proponents of a parallel mechanism of attention during reading is to delineate the parameters of such a framework.” From this perspective, the development of the first version SWIFT-I was important in order to keep the scientific debate open and to demonstrate a viable alternative to E-Z Reader and/or the principle of sequential attention shifts.

Once we have developed a mathematical model based on parallel processing of words, we can investigate the problem of serial versus parallel processing by computational means. We show later in this article that it is possible to introduce a continuous spectrum from strictly serial to fully parallel models by a parametrization of the type of processing. Thus, we show how a computational model might contribute to this long-standing research problem. In perspective, we hope to stimulate new experimental and theoretical work motivated by the results obtained from the SWIFT-II model.

Before we present our model and its mathematical analysis, we briefly review three theoretical approaches to the control of eye movements in reading, formulate the goals for our modeling approach, and present the core theoretical assumptions as a basis for the SWIFT-II model.

Models of Eye-Movement Control in Reading

During reading, saccadic eye movements are necessary to move words to the center of the visual field, the fovea, where high visual acuity enables efficient word recognition. Thus, reading may be looked upon as a case study in *active vision* (Findlay & Gilchrist, 2003), the notion that eye movements are essential for almost all visual perception.

Given the complexity of eye-movement patterns and the considerable amount of variance in fixation durations, it is unclear whether eye movements are directly guided by high-level language processes. With respect to model categorization, we are interested in the problem of whether *cognitive models,* mainly driven by language-related properties of words (e.g., word recognition), are more adequate than *primary oculomotor control* (POC) models. Models that fall into the latter category exploit low-level information (e.g., word length) to reproduce some of the basic patterns of eye movements. For example, Reilly and O’Regan (1998) assumed that the eye is directed to the longest word in the area of about 20 characters to the right of fixation and that oculomotor errors (e.g., overshoot or undershoot of the center of a target word) lead to properties of within-word corrections necessary for word recognition (see also O’Regan, 1990, 1992; O’Regan & Lévy-Schoen, 1987). McConkie, Kerr, and Dyre (1994) developed a two-state model, which provided a good account of within-word landing positions (McConkie, Kerr, Reddix, & Zola, 1988). It is important to note that effects of lexical processing on eye-movement control are not completely excluded in POC; however, it is assumed that these higher level influences only modulate a control strategy that is primarily based on low-level visual information.

Another recent primary oculomotor model was suggested by Yang and McConkie (2001, 2004). The key assumption of their competition–interaction theory is that the temporal aspect of saccade planning is basically independent of lexical processing. Processing difficulty, however, can inhibit the oculomotor system from initiating a saccade program.

To give new insights into the debate about cognitive versus POC models, it is necessary to develop a detailed model of eye-

[2] We refer to the first version as SWIFT-I. For direct comparisons, the current version of our model is labeled SWIFT-II.

movement control that integrates experimentally observed phenomena from both approaches. As an example, such a model should reproduce effects of word difficulty (e.g., measured by printed word frequency) as well as oculomotor effects (e.g., systematic errors in initial landing positions).

Following the terminology we proposed earlier (see Engbert et al., 2002), cognitive models may be further divided into subclasses according to their principles of allocation of visual attention. Two important concepts are control by *sequential attention shifts* (SAS) and *guidance by attentional gradients* (GAG).

SAS models are generally based on Morrison's (1984) proposal that covert shifts of attention are generically performed during fixation. On the basis of these attentional shifts, saccadic eye movements are prepared (Deubel & Schneider, 1996; Kowler, Anderson, Dosher, & Blaser, 1995; Kustov & Robinson, 1996). At the same time, parafoveal information is used to start word recognition. The mechanism of SAS provided a straightforward account of selective skipping of short high-frequency words.

The E-Z Reader model (Reichle et al., 1998) represents the most advanced attempt to build a theory of eye-movement control based on SAS. The development of this model was motivated by two important findings incompatible with Morrison's (1984) model. First, *preview benefit,* the shortening of processing time on subsequent words originating from time spent on the foveal word, is modulated by foveal processing load (Henderson & Ferreira, 1990; Kennison & Clifton, 1995). Second, one often observes "spillover" effects due to word frequency (Rayner & Duffy, 1986); that is, lower frequency words induce longer fixation durations not only locally but also lengthen the fixation duration on the succeeding word. Recent further developments of E-Z Reader include landing site distributions (Reichle et al., 1999) and improved refixation behavior (Reichle et al., 2003), thus extending the model to reproduce effects generated by oculomotor control principles, in addition to effects of lexical processing. The interface between cognition and eye-movement control in E-Z Reader was reevaluated recently (Pollatsek, Reichle, & Rayner, in press). In a variant of an SAS model, Engbert and Kliegl (2001) showed that it is possible to relax the strong assumption of lexically driven saccade programming. Therefore, the SAS framework is compatible with the assumption of autonomously generated saccades, saccades that are not induced by a lexical control loop.

In models based on GAG, there is a continuous distribution of lexical processing rate over the fixated region of text. Legge, Klitz, and Tjan (1997) proposed a gradient-type model with a saccade-targeting mechanism that minimizes the uncertainty about the current word, called the *ideal-observer* model of reading (see also Legge, Hooven, Klitz, Mansfield, & Tjan, 2002).

In SWIFT-I (Engbert et al., 2002), we proposed that four words are processed in parallel. Processing rate is highest for the foveal word and decreases to the parafoveal words to the left and to the right of the fixated word, and there is still some parafoveal processing on the second word to the right. Although this assumption was rather simplified without word lengths taken into account, this model turned out as a viable alternative to models based on the SAS principle. To extend the range of phenomena explained by SWIFT-II and to investigate the question of serial versus parallel processing of words, we develop an advanced version of SWIFT in this article. Before we start to explain the core principles of our new model, it is necessary to clarify the goals of our attempt to model the control of eye movements during reading.

Modeling Goals

The reduction of a real-world problem to a number of simple rules is among the key principles of mathematical modeling. The level of detail may vary across model components. As noted in a recent viewpoint article by May (2004), an approach that includes as many experimentally observed details as possible represents an abuse of mathematical modeling, because many of the known details of a problem may turn out to be irrelevant to the model and some important ingredients might be missing:

> Perhaps most common among abuses, and not always easy to recognize, are situations where mathematical models are constructed with an excruciating abundance of detail in some aspects, whilst other important facets of the problem are misty or a vital parameter is uncertain to within, at best, an order of magnitude. (p. 793)

As stated above, the main objective in our modeling approach is the interface of visual processing of words and eye-movement control. In mathematical models developed over the last few years, it turned out that the control of eye movements in reading can be captured by a theoretical model without integrating an advanced model of language processing (see Reichle et al., 2003). Most of the variance in eye-movement patterns and many of the experimental phenomena can be explained by models on the basis of rather simplified rules for word recognition and mechanisms for saccade programming. Thus, although language comprehension is the function of reading, many higher level linguistic processes essential to language comprehension typically have a rather small impact on the details of eye-movement control during reading. To make our modeling approach more transparent, we briefly discuss the experimentally observed phenomena that we attempt to reproduce with our model and how to evaluate the model's performance.

Quantitative Measures for Goodness of Fit

The performance of computational models can be evaluated by quantitative and qualitative measures. Eye-movement patterns clearly depend on properties of lexical difficulty, which is most commonly characterized by printed word frequency and word predictability (i.e., the probability of guessing a word from the sequence of previous words of the sentence; Kliegl, Grabner, Rolfs, & Engbert, 2004; see Rayner, 1998, for a review). Although printed word frequency can be computed from large text corpora and independent of context, word predictability incorporates many aspects of a reader's knowledge of language, depends strongly on context, and must therefore be estimated from experiments, obtained from incremental reading tasks, for each word of a given sentence. An important physical word parameter influencing eye-movement control is word length. For example, word-length information acquired parafoveally is used in computing the next saccade length (e.g., Morris, Rayner, & Pollatsek, 1990; O'Regan, 1979; Rayner, 1979). From these considerations, word frequency, word predictability, and word length will serve as independent variables for the analysis of dependent measures discussed in this section.

Among the quantitative measures for the control of eye movements in reading are temporal variables (fixation durations), spatial variables (probabilities for different types of saccades), and a number of experimentally observed effects, which mainly represent conditional variables, that is, more complicated combinations of spatial and temporal measures such as fixation durations conditional on the fixation location within a word.

Fixation durations. Inspection times are central for evaluating visual information processing in reading. An important measure for word difficulty is *gaze duration* (e.g., Rayner, 1998), the sum of the first fixation and all immediate refixation durations. Because of the large number of ways in which fixations sum up to gaze duration, gaze duration is an average measure over many different patterns of fixations, such as whether two successive fixations in a word occur in a forward or backward sequence. For a more detailed look into the model's dynamics, we aim at a representation of the experimental data by nonoverlapping measures.[3] Therefore, we separately calculate *single fixation duration* for all cases in which words receive one fixation. For the evaluation of refixations, we use *first fixation duration*[4] and *second fixation duration.* These measures are limited to first-pass reading (i.e., fixations after regressions to previous words do not contribute)—irrespective of whether this word had been skipped or fixated initially. Finally, we calculate *total reading time,* the sum of all fixations regardless of the eye's trajectory that generates these fixations.[5]

Fixation probabilities. The four measures of fixation durations are complemented by four measures of fixation probabilities. The fixation-probability measures characterize the spatial aspect of eye-movement patterns. On the basis of first-pass reading, we calculate *skipping probability,* the *probability for two fixations,* and the *probability for three or more fixations.*[6] Inasmuch as our model inherently produces interword regressions, we also calculate the *regression probability* or, more precisely, the probability that a word is the target of an interword regression.[7]

Effects of word length versus word frequency. Means of the above eight measures of fixation durations and fixation probabilities broken down by logarithmic word-frequency classes have achieved the status of benchmark data for the first cohort of computational models of eye-movement control in reading (e.g., Engbert & Kliegl, 2001; Engbert et al., 2002; Reichle et al., 1998). These summary statistics also proved useful for estimating model parameters. As effects of word length and word frequency are potentially variables of equal importance, however, we will compute model fits on the basis of individual words in this article. Thus, each word contributes a "data point" to the dependent variables. This opens the possibility for a detailed inspection of the model's performance on single sentences. Furthermore, by averaging over classes of word length and frequency, we can easily determine effects of word length and frequency based on the summary statistics of the earlier studies.

Within-word landing positions. An important impact of the oculomotor system on reading behavior arises from oculomotor errors. In addition to random errors, which occur in all motor systems, we observe a systematic component (McConkie et al., 1988). As a consequence, the *preferred viewing location* (Rayner, 1979) is a point left of the center of a word.

Effect of inverted optimal viewing position (IOVP) of fixation durations. As visual acuity decreases from the maximum in the center of the visual field (the fovea) to the parafovea and periphery, word recognition is fastest when fixating an isolated word in the center (O'Regan & Jacobs, 1992; O'Regan & Lévy-Schoen, 1987; O'Regan, Lévy-Schoen, Pynte, & Brugaillere, 1984). Contrary to this finding in isolated word recognition, Vitu, McConkie, Kerr, and O'Regan (2001; see also Nuthmann, Engbert, & Kliegl, 2005) reported for continuous reading that first and single fixation durations are longer for fixation positions in the word center than for fixation positions near word boundaries. Without further theoretical specification, this effect is opposite to predictions of cognitive models, which assume word recognition to be fastest (rather than slowest) near word centers.

In addition to the well-established phenomena described above, we also investigate model performance in relation to recent, still somewhat controversial, issues, because one major motivation for building mathematical models is to generate predictions for future research directions.

Fixation duration before word skipping. Fixation durations before skipped words provide a fingerprint for sequential allocation of attention, postulated in SAS models. The assumption that the default target of an automatically started saccade program is the next word implies that word skipping involves the cancelation of this saccade program and a restart of a new saccade program to the word beyond the next one. Such saccade cancelation increases fixation durations before skipped words; that is, it leads to skipping costs. In a recently published analysis, this theoretical prediction was not consistently supported with experimental data from continuous reading (Kliegl & Engbert, 2005). Therefore, we investigate fixation durations before word skipping as a model test.

Lag and successor effects. Fixation durations on a given word depend not only on the length, frequency, and predictability of the fixated word but also on these properties of the previous (i.e., lag) and the next (i.e., successor) words (Kliegl, Nuthmann, & Engbert, 2005). Indeed, lag effects are of similar strength to the effects of fixated word properties, inducing a longer average fixation duration on words following low-frequency, low-predictable, or long words. One of several possible interpretations of this phenomenon is that processing time spills over from word $n - 1$ to word n (e.g., Rayner & Duffy, 1986). Analogously, we can study successor effects of word $n + 1$ on fixation durations of word n, a subset of which are called *parafoveal-on-foveal* effects (Kennedy, 2000a, 2000b; Kennedy & Pynte, 2004). Mechanisms that reproduce these experimental observations might lead to qualitative differences between different models.

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[3] Nevertheless, we use gaze duration as a derived measure in Appendix D.

[4] In the following, we compute first fixation durations as an average of all cases with a second (or more) fixation, excluding single-fixation cases. Traditionally, however, first fixation durations include single-fixation cases (e.g., Rayner, 1998).

[5] This category is necessary to collect all possible fixation sequences in a "rest" category.

[6] By definition, the probability for a single fixation can be calculated by 1 minus the sum of the probability of skipping and the probabilities of two and three or more fixations.

[7] In the following, we use the expression *regression* for interword regressions exclusively; refixations oriented to the left are called *regressive refixations.*

Qualitative Aspects of Model Fitting

Several of the dependent variables mentioned above represent qualitative measures of model performance. For example, models may differ in (a) whether they account for regressions, (b) whether they reproduce the IOVP effect, (c) whether they exhibit costs for (or benefits from) word skipping, and (d) whether they reproduce patterns of lag and successor effects. Such qualitative aspects of model fitting are very important to test whether a model's mechanism for reproducing an experimentally observed effect is correct, whether it is the only possible explanation, and whether it is possible to develop alternative mechanisms.

Given the substantial amount of knowledge about the neural foundation of saccade generation, the neurophysiological plausibility of models of eye-movement control is a further qualitative criterion for the evaluation of theoretical models. A very general model for the generation of saccades has been proposed by Findlay and Walker (1999); this model is built on the assumption of two separate pathways concerned with the spatial and the temporal programming of eye movements. From this perspective, reading might be looked on as a case study for the control of eye movements in a well-structured environment. Therefore, we require that modeling assumptions should be special cases of the general principles proposed by Findlay and Walker.

Closely related to this point is model generalizability. In reading, eye movements are effectively one-dimensional along the horizontal axis (except for return sweeps to the next line of text). Here we can ask whether and how the model's control principles can be extended to two-dimensional trajectories, for example, in visual search. Ideally, a model for the control of eye movements in reading should be generalizable to and theoretically enrich the analysis of eye movements in visual search.

Core Concepts of Our Model

Before we present the detailed mathematical formulation, we summarize the core principles of the SWIFT-II model in brief statements (see Table 1). The principles are elaborated and discussed in detail in the following paragraphs.

Spatially distributed processing of an activation field (Principle 1): In our dynamic-field approach (e.g., Erlhagen & Schöner, 2002), all types of saccades are generated inherently to the model, as target selection is due to a competition among words with different activations. The parallel build-up of activations over several words implies that processing is distributed across several words at a time.

Table 1
Core Principles of the SWIFT Model

No.	Principle
1	Spatially distributed processing of an activation field
2	Separate pathways for saccade timing and saccade target selection
3	Random saccade generation with time-delayed foveal inhibition
4	Two-stage saccade programming with labile and nonlabile stages
5	Systematic and random errors in saccade lengths
6	Error correction of mislocated fixations
7	Modulation of saccade latency by saccade length

Separate pathways for saccade timing and saccade target selection (Principle 2): Motivated by neurophysiological findings, temporal and spatial aspects of saccade generation are controlled on different pathways (Findlay & Walker, 1999). Therefore, the problems of when to start the next saccade program and where to go next, are decoupled.

Autonomous saccade generation with time-delayed foveal inhibition (Principle 3): Saccade programs are generated autonomously, so that fixation durations are basically realizations of a random variable. This stochastic process is modulated by a foveal inhibition process to extend the inspection times for difficult words. Because this inhibitory process is based on a slower word-recognition circuit (compared with the short brainstem saccade generator; e.g., Carpenter, 2000), the inhibitory process includes a time delay.

Two-stage saccade programming with labile and nonlabile levels (Principle 4): Programming of saccades is a two-stage process, motivated by results from the double-step paradigm (Becker & Jürgens, 1979). During the labile stage, the oculomotor system is prepared for the next saccade program. A new initiation of a saccade program during the labile stage leads to a cancelation of the first saccade program and starts a new saccade program. At the end of the labile stage, the target is selected from the field of activations, a point-of-no-return is passed, and the saccade can no longer be canceled.

Systematic and random errors in saccade lengths (Principle 5): The oculomotor system inherently produces saccadic errors, that can be decomposed into systematic and random components (McConkie et al., 1988). As a consequence, in addition to random variability in fixation positions, systematic shifts in within-word landing position distributions as a function of launch-site distance are observed. Misguided saccades may also lead to fixations on unintended words (mislocated fixation, see below).

Error correction of mislocated fixations (Principle 6): Experimental data suggest and our simulations show that saccades frequently land on unintended words, which leads to mislocated fixations (Nuthmann et al., 2005; see also Rayner, Warren, Juhasz, & Liversedge, 2004). In this case, we assume that a new saccade program starts immediately, that is, the autonomous timer is overruled. The target of this saccade will be determined at the end of the labile saccade stage according to the general rule (Principle 4). This error-correcting mechanism can explain the IOVP effect of fixation durations.

Modulation of saccade latency by intended saccade amplitude (Principle 7): As a final principle, we assume that saccade latency is modulated by the amplitude of the intended saccade. Because in our model saccade target selection is performed at the end of the labile stage of the saccade program—the intended saccade amplitude is computed at the end of the labile stage—only the nonlabile stage can be influenced by the intended saccade amplitude. We will show that this principle, which is motivated by basic oculomotor research (e.g., Wyman & Steinman, 1973), contributes to the explanation of the IOVP effect in fixation durations.

Given the core principles, there is no unique way for a translation into mathematics, of course. Therefore, we discuss the specific choice of mathematical equations in the next section. Once formulated mathematically, we can implement the model on a computer to generate artificial data, which can be analyzed using the same algorithms as applied for the analysis of experimental data.

Moreover, semianalytical techniques may add to our understanding of the control principles underlying eye movements in reading (e.g., Engbert & Kliegl, 2003a).

Mathematical Formulation of the Model

Dynamic Field of Activations

Our model is a cognitive model with word recognition driving eye movements. In SWIFT, a one-dimensional field of activations $\{a_n(t)\}$ for words $n = 1, 2, 3, \ldots, N_w$ at time t functions as a saliency map, from which potential saccade targets are computed (Principle 1). It is no limitation of the formalism that the number of words, N_w, in a given sentence is unknown when reading the first words of the sentence, as the number of words could be specified later in the reading process. Furthermore, it will turn out that word j with index $j \geq n + 4$ typically has close to zero activation during fixation on word n. Thus, there is a limited horizon of saccade targets constrained by target selection probabilities at any time.[8]

The activation field $\{a_n(t)\}$ changes over time because of word recognition. Activation is built up in a preprocessing stage and decreases during a later lexical completion process. The relative amount of activation will determine the probability that a word is selected as a saccade target. It is important to note the dynamical nature of the interplay between lexical processing and eye-movement control. Fixation position has a strong impact on word-recognition time, which determines the temporal evolution of the activation field. Because the activation field determines saccade targets, our model inherently exhibits historicity, that is, a strong dependence on the previous sequence of fixations. Historicity is a key property of nonlinear dynamical systems. Formulated from a general mathematical viewpoint, nonlinearity of the underlying equations in SWIFT adds a new source of complexity in eye movements to the stochastic origins in previous models (Engbert, Kliegl, & Longtin, 2004).

Word Difficulty

The assumption of an activation field still leaves open how lexical difficulty of words is represented. Here we assume that the maximum activation L_n of word n is related to the word's processing difficulty. Our approach to this problem is based on a proposal by Reichle et al. (1998) that word difficulty depends on printed word frequency (per million words) and predictability. Previous theoretical models were based on a multiplicative interaction of word frequency and predictability (Engbert & Kliegl, 2001, 2003b; Engbert et al., 2002, 2004; Reichle et al., 1998, 1999, 2003).

Recently, Rayner, Ashby, Pollatsek, and Reichle (2004) published an experimental study demonstrating that fixation durations only mildly departed from an additive combination of word frequency and predictability: Predictability effects were larger for low-frequency than for high-frequency words. Additional numerical simulations using different variants of the E-Z Reader model indicated that an additive model of word frequency and predictability fit better than the previous multiplicative one. Thus, Rayner et al.'s (2004) results suggest that the specific mathematical interaction of word frequency and predictability is additive (or a mixture of additive and multiplicative) rather than strictly multiplicative.

Here, we propose an alternative view on the interaction of word frequency and predictability. The combination of word frequency f_n and predictability p_n of word n in a single equation for word difficulty might be problematic because of the temporal characteristics inherent in the two variables. Whereas word frequency information unfolds during the word-recognition process, word predictability is by definition independent of visual input. Thus, we suggest different processes of how the two variables generate certain modulations of processing times. First, we assume that word difficulty—as a variable in our model—can be estimated from word frequency alone, that is,

$$L_n = \alpha\left(1 + \beta \frac{\log f_n}{F}\right), \tag{1}$$

where α is the intercept value of the lexical access time, which is modulated by the (natural) logarithm of word frequency, f_n, with slope parameter β. The constant $F = 11$ is used to scale the values of $\log f_n$ to a range in the interval [0; 1], so that the coefficient β is dimensionless and characterizes the strength of the frequency effect.

Second, we assume that word predictability modulates processing rates. As a consequence, the impact of predictability p_n on the time course of processing of word n might be earlier than the impact of word frequency. The mathematical implementation of these processes is described below in the section on the equation of motion of our model. We speculate that such a process dissociation underlying effects of word frequency and predictability will yield neither a strictly additive nor a strictly multiplicative interaction, which could be compatible with the above experimental results by Rayner et al. (2004).

Lexical Processing Rate

For spatially distributed processing, we assume that lexical processing rate, denoted by $\lambda > 0$, is a function of the distance (eccentricity) of a word to the current fixation position. This distance must be a function of the eccentricities of all letters of the word. We show later that this assumption has strong implications for spatial aspects of lexical processing.

The fixation position at time t is denoted by $k(t)$, where the range of k can be from 1 to the number of all characters, spaces, and punctuation marks in the sentence.[9] Motivated by the well-known bias of processing in the direction of reading, fixations on the spaces between words are counted as fixations on the words to the right of the spaces. The processing rate of word n is a function of processing rates of all letters $j = 1, 2, 3, \ldots, M_n$, where M_n is the number of letters of word n. We assume that processing speed is mainly limited by visual acuity, which is a function of the distance from the center of the visual field (i.e., the fovea). The distance of letter j of word n from the current fixation position is given by the eccentricity

[8] Note that this horizon is the result of the model's dynamics, not an ad hoc choice in building the model.

[9] In the first version of our model (Engbert et al., 2002), we neglected word length, and fixation position k was the index of the fixated word.

$$\epsilon_{nj}(t) = x_{nj} - k(t), \tag{2}$$

where x_{nj} is the position of letter j of word n. Lexical processing rate is a function of eccentricity, $\lambda \equiv \lambda(\epsilon)$. The size of the perceptual span decreases from at least 10 letters in central vision to 1.7 letters at an eccentricity of 15° (Legge, Mansfield, & Chung, 2001). This decrease is related to a corresponding reduction of reading rate. Because of the asymmetry of the perceptual span (McConkie & Rayner, 1976; Rayner, Well, & Pollatsek, 1980), we assume an asymmetric Gaussian function as the mathematical relation between lexical processing rate and eccentricity, that is,

$$\lambda(\epsilon) = \lambda_0 \exp\left(-\frac{\epsilon^2}{2\sigma^2}\right) \quad \text{with} \quad \begin{cases} \sigma = \sigma_L, & \text{if} \quad \epsilon < 0 \\ \sigma = \sigma_R, & \text{if} \quad \epsilon \geq 0 \end{cases}, \tag{3}$$

where σ_L characterizes the extension of the processing rate to the left and σ_R applies to the processing of letters to the right of the current fixation position (see Figure 1). The normalization constant λ_0 of the lexical processing rate function, Equation 3, can easily be calculated from the normalization condition

$$1 = \int_{-\infty}^{+\infty} \lambda(\epsilon)\mathrm{d}\epsilon = \int_{-\infty}^{0} \lambda_0 \exp\left(-\frac{\epsilon^2}{2\sigma_L^2}\right)\mathrm{d}\epsilon + \int_{0}^{+\infty} \lambda_0 \exp\left(-\frac{\epsilon^2}{2\sigma_R^2}\right)\mathrm{d}\epsilon, \tag{4}$$

which yields the relation[10]

$$\lambda_0 = \sqrt{\frac{2}{\pi}} \frac{1}{\sigma_R + \sigma_L}. \tag{5}$$

Using the normalization, total lexical processing rate is fixed at a constant value of 1. This value is the theoretical maximum of lexical processing rate, which can be reached if letters are arranged along the horizontal axis from $-\infty$ to $+\infty$. In a realistic situation, this will never occur, of course. Thus, the total lexical processing rate will effectively be bounded between 0 and 1.

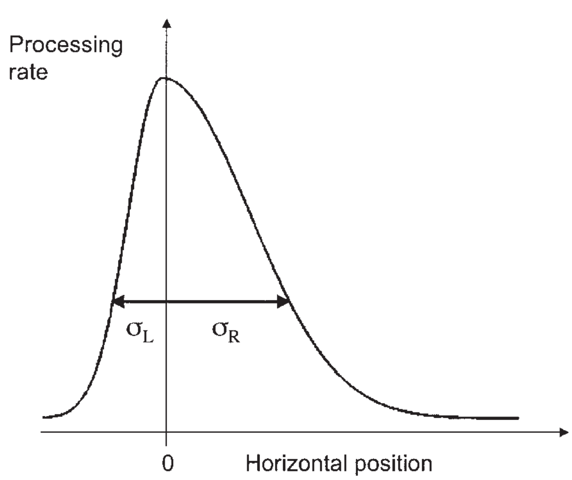

Figure 1. Lexical processing rate is assumed to follow an asymmetric Gaussian distribution with different parameters, σ_L and σ_R, to the left and to the right of the fixation point, respectively.

Given our assumption on lexical processing rate for letters (Equation 3), we now have to specify how the processing rate of a word can be calculated from the set of processing rates of all its letters. Two special cases for word-based processing rates can be distinguished: The lexical processing rate of a word is (a) the sum of the rates of all its letters or (b) the mean of all of its letters. In the first case, every additional letter would be a processing advantage, as it can potentially help to enhance word recognition. In the second case, however, every additional letter leads to processing costs. Because of these very different views, we use a parametrized function, which includes both (a) and (b) as special cases,

$$\lambda_n(t) = (M_n)^{-\eta} \sum_{j=1}^{M_n} \lambda(\epsilon_{nj}(t)), \tag{6}$$

where for $\eta = 0$, the processing rate of the word is the sum of the rates of all letters, and for $\eta = 1$, it is the mean of the rates of all letters. Using numerical simulations, we show below that—under the assumptions made here—the actual value of η is an intermediate value between the two extreme cases.

The asymmetry of the distribution of lexical processing rate (Equation 3) for $\sigma_R \neq \sigma_L$ leads to a shift of the maximum of lexical rate to the left (see Figure 2). This result is qualitatively in agreement with experimental observations: First, the *preferred viewing location* (Rayner, 1979) is indicated by the maximum of the distribution of initial fixations on a word, which shows a shift to the left from the word center. Second, the *optimal viewing position* (OVP) is determined as the position of the minimum of recognition time (for studies of isolated word recognition, see O'Regan & Jacobs, 1992; O'Regan & Lévy-Schoen, 1987; O'Regan, Lévy-Schoen, Pynte, & Brugaillere, 1984) and/or the position of the minimum of refixation probability. In our data, this minimum turned out to be close to the word center with a leftward bias, too (Nuthmann et al., 2005).[11] The interesting question is whether this leftward tendency is functional or whether it is related to systematic errors of the oculomotor system. As illustrated in Figure 2, our assumptions on word processing yield a maximum of the processing rate shifted to the left from word center. Thus, our concept of how lexical processing rates of words are calculated from rates of letters is highly compatible with the experimental observations of a leftward shift of the preferred viewing location.

Temporal Evolution: Equation of Motion

In our model, the activation field can be interpreted as a map of visual salience (e.g., Findlay & Walker, 1999). Before processing, the word is unknown, and after processing, the word is completely processed, which is in both cases related to an activation of zero. During preprocessing, activation $a_n(t)$ of word n increases to its maximum value L_n. The time to reach the maximum is denoted by $t_p(n)$. *Preprocessing* is defined as the first stage of processing in

[10] Here we use the normalization formula of the Gaussian distribution:

$$\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} \exp\left(-\frac{x^2}{2\sigma^2}\right)\mathrm{d}x = 1.$$

[11] McConkie, Kerr, Reddix, Zola, and Jacobs (1989), however, reported a small rightward bias.

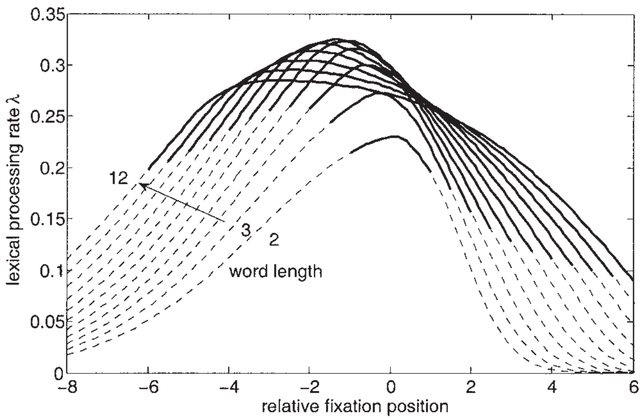

Figure 2. Lexical processing rate as a function of word length and fixation position relative to word center. The within-word maxima are shifted to the left with increasing word length. For $\eta = 0.5$, lexical processing rate shows an absolute maximum of $\lambda = 0.32$ at relative fixation position $k = -1.37$ for word length 7. In this example, the parameters of the asymmetric Gaussian are chosen as $\sigma_R = 3.6$ letters and $\sigma_L = 1.4$ letters. The bold lines correspond to within-word fixation positions; the dashed lines indicate fixation positions beyond the word edges.

our model.[12] In a second stage, called *lexical completion,* the activation tends to zero until it is completely processed. An additional process is decay of activation, assuming a nonidealized memory with leakage.

The temporal evolution of activations during reading of a sentence consisting of N_w words is governed by a system of N_w coupled ordinary differential equations (ODEs),

$$\frac{\mathrm{d}a_n(t)}{\mathrm{d}t} = F_n(t)\Lambda_n(t) - \omega, \tag{7}$$

where

- $F_n(t)$ is a preprocessing factor, modulated by predictability,
- $\Lambda_n(t)$ is a stochastic variable for processing rate, and
- ω gives the strength of the global decay process.

Now we discuss these three processes in more detail. The decay process is introduced as a global parameter, which induces a slow decrease of activations of all words with a constant rate and may be interpreted as a memory leakage, which prevents the exact tracking of processing states for all words.

The preprocessing factor $F_n(t)$ introduces an asymmetry between preprocessing and lexical completion, which is also modulated by predictability. First, during preprocessing, preliminary information on a specific word will be accumulated for potential target selection. The preprocessing factor introduces an asymmetry with a fast increase and a slower decrease of activation. The question of how much lexical (orthographic or semantic) information can be accessed using parafoveal information is an open research problem and clearly beyond the scope of the current article (see Rayner & Juhasz, 2004, for a recent review). We return to this problem below. We would like to comment here that preprocessing of a word is a rather preliminary stage of processing in our model, which mainly adds the word to the set of possible saccade targets, that is, all words with $a_n(t) > 0$.

Second, as noted above in the section on word difficulty, we assume that the predictability p_n of word n modulates the processing rate. We assume that for high-predictable words, that is, with p_n close to 1, processing rate is decreased during preprocessing as long as the word is not fixated. This assumption is motivated by the fact that for a high-predictable word there is a high probability that the word can be guessed without (or with minimal) visual input. As a consequence, the activation of a parafoveal high-predictable word should build up more slowly than the activation of a parafoveal low-predictable word. Because activations represent a measure for target selection probability in our model, there will be a higher skipping probability for high-predictable words. Because word recognition will be faster for high-predictable words than for low-predictable words, however, we assume that processing rate increases with predictability once the word is in the lexical completion state, that is, the state with decreasing activation. Mathematically we formulate these mechanisms as

$$F_n(t) = \begin{cases} +f(1 - \theta p_n) & \text{if} \quad t < t_p(n) \quad \text{and} \quad k < n \\ \quad \text{(parafoveal preprocessing)} & \\ +f & \text{if} \quad t < t_p(n) \quad \text{and} \quad k \geq n \\ \quad \text{(foveal preprocessing)} & \\ -(1 + \theta p_n) & \text{if} \quad t \geq t_p(n) \\ \quad \text{(lexical completion)} & \end{cases}, \tag{8}$$

where $f > 1$ indicates that preprocessing is faster than lexical completion and the factors $(1 \pm \theta p_n)$ generate the proposed modulations by predictability.

Finally, lexical completion is implemented as a memory-retrieval process, which is known to be inherently stochastic (e.g., Ratcliff, 1978). As a consequence, we explicitly simulate a random walk for the temporal evolution of activations, that is, for both preprocessing and lexical completion. Therefore, we assume that the lexical processing rate $\lambda_n(t)$ of word n fluctuates around its mean with a standard deviation proportional to its mean,

$$\Lambda_n(t) = \lambda_n(t)(1 + \varphi\xi_t), \tag{9}$$

where ξ_t represents Gaussian noise with zero mean and a standard deviation of one. Noise samples are uncorrelated between integration time steps. For all simulations presented here, we chose $\varphi = 2$, which produces a reasonable amount of stochasticity in word recognition. An example for the resulting stochastic activation process is illustrated in Figure 3.[13]

Saccade Target Selection

Given the principles for the temporal evolution of the set of lexical activations, $\{a_n(t)\}$, assumptions on saccade target selection are straightforward.[14] Saccade target selection is a competitive process among all activated words, that is, among all words with

[12] Note that the distinction between preprocessing and lexical completion does not refer to parafoveal versus foveal processing.

[13] For a study of the role of noise in a model of eye-movement control, see Engbert and Kliegl (2003b).

[14] Whereas the lexical processing assumption had to be modified strongly because of letter-based metrics of words in the new version of our model, the mechanism of saccade target selection is effectively the same as in the first version of our model (Engbert et al., 2002).

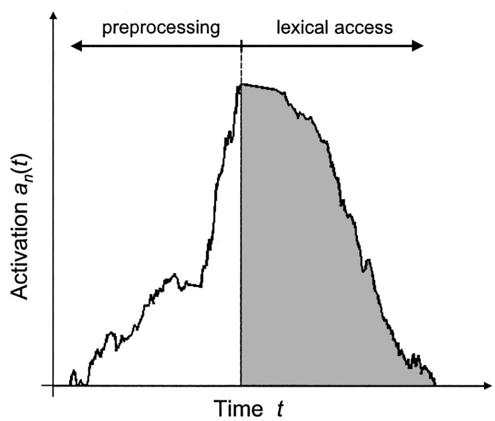

Figure 3. Illustration of the time evolution of stochastic activation by the equations of motion (Equations 7–9). The activation is a random-walk model, which accounts for the inherent stochasticity in the memory-retrieval process underlying word identification.

$a_n(t) > 0$. As a consequence, if words are activated in parallel substantially,[15] the model can potentially generate all types of saccades observed in experiments (e.g., word skipping, refixations).

In mathematical terms, we assume that target selection is a stochastic process. The probability $\pi(n, t)$ to select word n as a saccade target at time t is given by its relative lexical activation,

$$\pi(n, t) = \frac{a_n^\gamma(t)}{\sum_{j=1}^{N_w} a_j^\gamma(t)}, \tag{10}$$

where the exponent γ is a measure for the stochasticity in the target selection process. We can consider two special or extreme cases of how target words are selected,

- $\gamma = 0$: Target selection probability for all words with nonzero lexical activation is equal (random target selection), and
- $\gamma \to \infty$: Target selection is deterministic; the word with highest activation is the next saccade target ("winner-takes-all").

Previous simulations have shown that $\gamma = 1$ gives the best fits. In this case, target selection probability is proportional to relative lexical activation, which is known as Luce's (unbiased) choice rule (Luce, 1959).

Control of Fixation Duration by Foveal Inhibition

According to Principle 3, saccade timing is a stochastic process, which is modulated by the amount of foveal activation. We assume that the time interval between two commands to initiate a saccade program is purely stochastic with a predefined mean t_{sac}, which is related to a reader's individual reading rate. The inhibitory modulation of this random process will be derived in two steps.

First, the fixation duration on word n is modulated by the amount of foveal activation. Let us denote the time of initiation of the saccade program for saccade i by t_i. The next command for starting a new saccade program $i + 1$ will happen after a stochastic interval Δt_{i+1} with mean value t_{sac}. This interval will, however, be procrastinated by an inhibitory top-down signal from the lexical processing module. The next command for starting saccade program $i + 1$ is generated, if

$$t > t_i + \Delta t_{i+1} + h a_k(t), \tag{11}$$

where h gives the strength of the foveal inhibition process. Note that the prolongation is limited even for arbitrarily high values of the constant h. Using an analytical approximation (Kliegl & Engbert, 2003), we have shown that the maximum inhibition time T is given by

$$T = \frac{\alpha}{\lambda(0) + 1/h} \xrightarrow{h \to \infty} \frac{\alpha}{\lambda(0)}, \tag{12}$$

where $\lambda(0)$ is the foveal processing rate defined in SWIFT-I (Engbert et al., 2002).

Second, processes of word recognition are much slower than the fast brainstem saccade generator (e.g., Sparks, 2002). Therefore, word recognition can impact the saccadic system only with a time delay. This assumption is motivated by the plausibility argument that the module for lexical processing performing word recognition is physiologically separated from the oculomotor nuclei of the brainstem, which will produce a time delay for the impact of processing difficulty on the control of fixation durations. To suppress noise, we introduce an additional integral average over the interval from $t - \tau$ to 0 for the inhibition process and replace Equation 11 by

$$t > t_i + \Delta t_{i+1} + h[a_k]_\tau, \tag{13}$$

where

$$[a_k]_\tau \equiv \frac{1}{\tau}\int_{t-\tau}^{0} a_{k(t')}\mathrm{d}t'. \tag{14}$$

Thus, the average delay is $\tau/2$. An important property of this implementation is that for a time delay of the order of the average fixation time, the evaluated activation in Equation 14 refers to a previous fixation, which frequently occurred on the previous word. Thus, the concept of time-delayed foveal inhibition can potentially explain lag effects of processing.[16]

Saccade Programming

Programming of saccades is a two-stage process involving a labile and a nonlabile stage. First, after starting a saccade program, a labile stage with an average duration τ_{lab} is entered. If there is another saccade command in this period of time, the labile stage can be canceled. In principle, saccade cancelation can happen successively. Using numerical simulations of our model, we found that 90.0% of all saccades are not canceled during the labile stage, 8.6% are canceled once, and 1.1% are canceled twice (all other cases are negligible).

[15] The degree of parallel activation is not only a question of the model architecture. It will depend on the values of model parameters.

[16] A simpler but both psychologically and neurophysiologically less plausible generalization of foveal inhibition would have been to add a new term $+h_1 a_{k-1}(t)$ to the right-hand side of Equation 11.

Second, the nonlabile stage with average duration τ_{nl} is entered after the labile stage terminates. The transition from labile to nonlabile stage triggers the target selection process (Equation 10). The two-stage organization is illustrated in Figure 4. The saccade execution is included in the model with average duration τ_{ex}.

During saccades, sensitivity to visual input is reduced, an effect called *saccadic suppression* (Matin, 1974). Because visual input stops during saccades, preprocessing is paused in SWIFT. Because of an eye-to-brain lag of approximately 50 ms (e.g., Foxe & Simpson, 2002; see also Reichle et al., 2003), preprocessing is interrupted for the duration of the saccade with a temporal delay of 50 ms (for both onset and offset of the saccade).[17] Because lexical completion should not depend critically on new visual input, we assume that lexical completion continues during saccades.

In the context of programming of saccades during reading, the assumption of two stages was first introduced by Reichle et al. (1998; see also Engbert & Kliegl, 2001) and later used in SWIFT-I (Engbert et al., 2002). The main motivation for the assumption derives from the double-step paradigm in saccade generation (Becker & Jürgens, 1979), which was used to demonstrate that presentation of a second target earlier than approximately 250 ms after the first could induce a cancelation of the saccade to the first target. A later presentation, however, led to fixations of both targets in a sequence. This effect is captured by passing a "point-of-no-return" at the transition from labile to nonlabile stages of saccade programming in our model.

Oculomotor Errors in Saccade Generation

Our assumptions on saccadic errors inherent to the oculomotor system are based on results by McConkie et al. (1988). The theoretical assumption underlying their analyses was that saccades are directed toward the center of a target word. These saccades, however, are modified by random as well as systematic error components, so that, on average, a small deviation of the initial landing position from the word center is observed. The systematic error component is known as the *range effect* (see also Kapoula, 1985; Poulton, 1981). Let us denote the *intended saccade amplitude,* the distance to the optimal viewing position of the next target word, by A. The realized saccade length l is given by the sum of the intended saccade amplitude A and two error terms,

$$l = A + l_{SRE} + l_G, \tag{15}$$

where l_{SRE} is called the *saccade range error* (systematic error) and l_G is Gaussian-distributed random error with zero mean.

The systematic deviation of the saccade length l from the intended saccade amplitude A can be interpreted as a limited adaptivity of the oculomotor system to arbitrary saccade lengths. If the intended saccade amplitude A differs from an optimal saccade amplitude A_0, we observe undershoot for $A > A_0$ and overshoot for $A < A_0$. In a linear approximation of this effect, we can write the saccade range error as

$$l_{SRE} = \delta_{SRE}(A_0 - |A|), \tag{16}$$

where δ_{SRE} gives the strength of the saccade range error.

The oculomotor noise is a Gaussian-distributed random component of the saccadic errors with zero mean. Generally, we observe an increase in random errors with movement amplitude in almost all processes of motor control (Poulton, 1981). For simplicity, we assume, again in a linear approximation, that the standard deviation of the random error can be approximated by the linear relation

$$\sigma_G = \delta_0 + \delta_1|A|. \tag{17}$$

From the perspective of minimal modeling, we aim at a model with as few parameters as possible. Fortunately, oculomotor errors do not add free parameters to the model, as all parameters in Equations 16 and 17 can be estimated directly from experimental data (McConkie et al., 1988). The four parameters (δ_{SRE}, A_0, δ_0, and δ_1), however, may have different values for forward saccades, refixations, and regressions. Using the data obtained on the Potsdam Sentence Corpus (Kliegl et al., 2005), we estimated the parameters of the saccade range error separately for these three types of saccades and used the same value in the case of the random error component (see Table 2). The result indicates that the parameters are very similar for forward saccades and refixations.[18] For regression, we observe a much smaller coefficient, δ_{SRE}, which is in agreement with Radach and McConkie's (1998) observation of a negligible saccade range error for interword regressions.

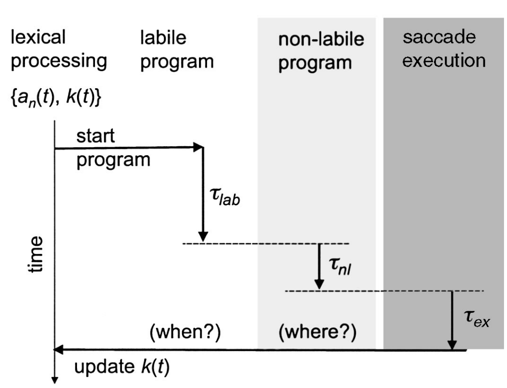

Figure 4. Temporal scheme of saccade programming. After the start of the saccade program, a labile (*lab*) stage is entered, which signals the engagement of the oculomotor system. At the end of the labile stage, the saccade target is determined and the saccade can no longer be canceled during the nonlabile (*nl*) stage. Finally, the saccade is executed (*ex*) and the fixation position shifts to a new position.

Mislocated Fixations and Error Correction

In the previous section, we discussed oculomotor errors in saccade generation with systematic and random components. Although even small errors will influence processing rates due to our assumption of a processing gradient, which is limited by visual acuity, saccadic undershoot and overshoot can lead to fixations on unintended words (see Figure 5). These *mislocated fixations* are most likely to happen close to word boundaries (Nuthmann et al., 2005). We assume that these misguided saccades are immediately corrected by starting a new saccade program, if there is currently

[17] Using numerical simulations, we found no significant impact of the eye-to-brain lag on our results. We kept this assumption, however, for physiological plausibility.

[18] The negative sign of the factor δ_{SRE} is due to the definition of the saccade range error in Equation 16.

Table 2
Parameter Values for Oculomotor Error Relations

Error type	Parameter	Forward saccade	Forward refixation	Regressive refixation	Regression	Reference
Saccade	δ_{SRE}	0.41	0.49	−0.5	−0.15	Equation 16
Range error	A_0	5.4	5.7	4.3	10.0	Equation 16
Gaussian	δ_0		0.87			Equation 17
Random error	δ_1		0.084			Equation 17

no labile saccade program active.[19] To implement this assumption in the simulation algorithm, we introduce a vanishing intersaccade interval,

$$\Delta t_i^{misloc} = 0, \tag{18}$$

for mislocated fixations. Thus, the mean interval between two saccade program initiations, Δt_i, will be shortened by this mechanism.

On average, the shortening of the intersaccade interval will induce a decreased fixation duration close to word boundaries—at beginnings and ends of words—which was observed in the IOVP effect of fixation duration by Vitu et al. (2001). Generally, such a mechanism is compatible with all models of eye-movement control that (a) specify a target word for each saccade and (b) include oculomotor errors (see Nuthmann et al., 2005 for details).

What are potential mechanisms for the immediate start of an error-correcting saccade program? It is commonly accepted that saccade amplitudes are determined by population-coded activations in the superior colliculus (e.g., Sparks, 2002, for a recent review). Accordingly, a single saccade is controlled by an efference copy of the motor signal to the eye muscles (Carpenter, 2000; Wurtz, 1996). Thus, errors are monitored during saccades. Recently, the idea that activation in the superior colliculus represents saccade vectors was challenged by Bergeron, Matsuo, and Guitton (2003), who demonstrated that collicular activation is related to gaze error in multistep gaze shifts. Regardless of whether saccade steps during reading are best described as single movements or multistep vectors (see also Krauzlis & Carello, 2003), the bottom-line from our current knowledge on the function of motor maps in the superior colliculi is that gaze errors are monitored continuously, which potentially provides a very fast detection of saccade errors. Thus, neurophysiological findings support the fast error-correction mechanism assumed in our model.

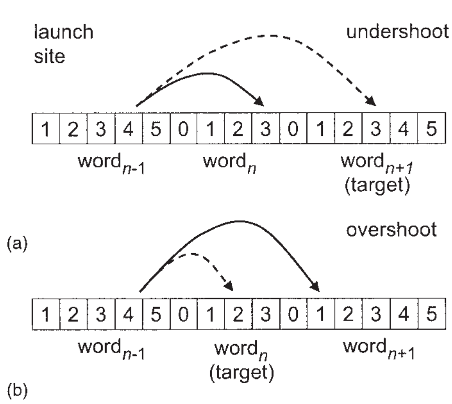

Figure 5. Saccadic undershoot and overshoot can result in fixations on unintended words (mislocated fixations). (a) Unintended forward saccade due to undershoot. (b) Unintended skipping due to overshoot.

Saccade Latency Modulation

The error-correction mechanism in case of mislocated fixations discussed in the previous section will lead to decreased fixation durations near word boundaries. This effect, however, will turn out to be more pronounced in experimental data compared with model simulations for first fixations. Assuming that the center of the word is the unique saccade target, the programming of a refixation with a first fixation placed very close to the word center is a very special situation, in which the intended saccade amplitude is rather small (i.e., one to two letters). Thus, if we assume an increased saccade programming time for small intended saccade amplitudes, we can explain the pronounced peak in first fixation durations. A basic dependence of saccade latency on intended amplitude has been demonstrated in several studies (Adams, Wood, & Carpenter, 2000; Kalesnykas & Hallett, 1994; Wyman & Steinman, 1973). It seems appropriate to remark, however, that such an effect will be very difficult to test experimentally in continuous reading.

From these considerations, we introduce a modulation of saccade programming time by intended saccade amplitude. In principle, such a modulation could occur at all stages of saccade generation, that is at the level of intersaccade intervals or the labile and nonlabile program stages. In SWIFT, the most likely saccade target can be read off from the activation fields any time this information is required. For simplicity, we assume that the nonlabile saccade stage, τ_{nl}, is affected by the intended saccade amplitude, A, that is, that the modulation occurs after target selection.

The impact of a dependence $\tau_{nl} = \tau_{nl}(A)$ on reading behavior depends on the range of the intended saccade amplitude A considered. For short amplitudes, $A \lesssim 4$, the saccades are mainly intraword movements, whereas for longer amplitudes, $A \gtrsim 6$, most saccades are interword movements to the right. Therefore, for short saccades the functional relation $\tau_{nl}(A)$ will modulate the IOVP effect, whereas for longer saccades the relation will affect successor effects, because a decreasing saccade latency with increasing intended saccade amplitude will produce shorter fixation durations before long parafoveal words compared with short parafoveal words. Consequently, it will be very difficult to disen-

[19] If there is already an active saccade program, the process of (potential) error correction cannot be accelerated.

tangle latency modulation from effects of lexical processing experimentally.[20]

For simplicity, we assume that the average duration of the nonlabile saccade stage is a Gaussian-type function of the intended saccade amplitude A,

$$\tau_{nl}(A) = \tau_{nl}^0 + \kappa_0 \exp(-\kappa_1 A^2), \tag{19}$$

where the parameter τ_{nl}^0 is the average asymptotic nonlabile saccade programming time, κ_0 represents the strength of the modulation, and κ_1 determines the width of the modulation by the intended saccade amplitude. In all simulations presented here, we fix κ_1 at a value of 0.1.

Stochasticity in Saccade Programming

After the nonlabile stage of saccade programming terminates, the saccade will be executed. We assumed that the mean saccade execution time is $\tau_{ex} = 25$ ms. For the simulation of noise in both saccade programming and saccade execution, we use a gamma distribution with a relation between standard deviation and mean of 1/3, a gamma distribution of 8th order.

Model Overview

In this section, we briefly summarize how the different subsystems of our model are orchestrated (see Figure 6) before we address the numerical simulations of the model. Word recognition is implemented as a spatially distributed process (Principle 1). A set of lexical activations keeps track of the actual state of word processing and controls saccade target selection ("where") and saccade timing ("when") via foveal inhibition using two separate pathways (Principle 2). The lexical decision circuit, which is a cortical long-loop control system compared with the brainstem saccade generator, can influence saccade timing by foveal inhibition only with a time delay τ (Principle 3). Saccade programming is a two-stage process (Principle 4). After a labile stage, a point of no return is passed and the nonlabile stage is entered. Target selection occurs at the transition from labile to nonlabile stage.[21]

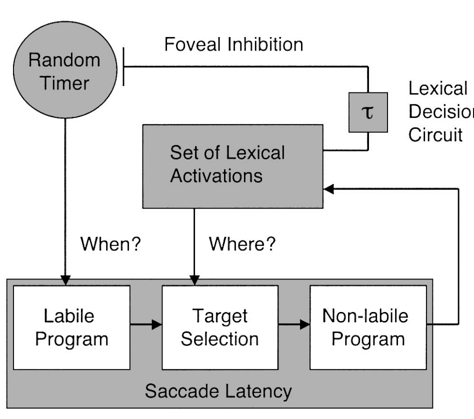

Figure 6. Model overview. A basic principle of SWIFT is that spatial ("where") and temporal ("when") pathways of saccade programming are separated.

Numerical Simulations and Model Parameters

On the basis of Principles 1 to 7 of the model (see Table 1), we discussed the precise mathematical formulation and some motivations for the underlying assumptions in the last section. Next, we carry out numerical simulations to fit the model's parameters and to compare the model's performance with experimental data.[22] Compared with the first version SWIFT-I (Engbert et al., 2002), we completely redesigned the numerical and statistical procedures and proposed a new and more detailed test of computational models of eye-movement control in reading.

First, we used a recently published experimental study with the Potsdam Sentence Corpus (for details on the sentence corpus, see Kliegl et al., 2004), which was meanwhile extended from 65 to 222 participants (Kliegl et al., 2005). With this amount of experimental data, we were able to analyze all of the discussed phenomena *on the same data set.* Because many effects are produced by highly nonlinear interactions, deviations in one empirical observable can potentially produce considerable deviations in other measures. Therefore, a strong test of model performance must be based on a single complete data set.[23]

Second, we computed all experimental measures for each word. The Potsdam Sentence Corpus consists of 1,138 words from 144 sentences. For statistical analyses, we currently exclude the first and last words from each sentence from our analysis. Therefore, we obtained a maximum of eight measures (four fixation durations and four fixation probabilities) for each of 850 words, yielding a total of 6,800 data points for model fitting. This procedure is a major advantage compared with the parameter-fitting procedures used for SWIFT-I and E-Z Reader 1–7. In these analyses, for only six measures (three fixation durations and three fixation probabilities), statistical averages were calculated on the basis of five classes of word frequency, yielding an empirical basis of 30 data points. The possible range of data patterns that could be explained by those models was very limited because of nonlinear interactions of parameters. Therefore, although we still believe that the previous method produced reliable results, we clearly suggest that the procedure proposed here should be used in future modeling studies.

Third, given the word-based nature of the measures, we computed chi-square-type statistics to evaluate the model (see Appendix A for details). Furthermore, we investigated effects of word frequency, predictability, and word length by averaging word-based measures over classes. Finally, we tested more specific effects (e.g., IOVP, lag effects) based on the same simulated data set.

[20] Note, however, that with our choice of $\kappa_1 = 0.1$ in Equation 19, latency modulation will predominantly affect IOVP effects in our model.

[21] Principles 5 to 7 (see Table 1) are related to saccadic errors and saccade program latencies; we did not include these principles in the schematic diagram of SWIFT organization in Figure 6.

[22] The implementation of SWIFT-II used in this article is available at http://www.psych.uni-potsdam.de/computational/

[23] This principle was not implemented in tests of the E-Z Reader model. As an example, McConkie et al.'s (1988) results on initial landing positions were combined with statistics of fixation durations obtained by Schilling, Rayner, and Chumbley (1998).

Table 3
Model Parameters

Parameter	Symbol	Value	Error	Min	Max	Reference
Lexical parameters						
Frequency, intercept	α	63.5	2.0	10	150	Equation 1
Frequency, slope	β	−0.20	0.03	−0.5	0	Equation 1
Predictability	θ	0.11	0.09	0	1	Equation 8
Visual processing						
Visual span, right	σ_R	3.74	0.08	1	7	Equation 3
Visual span, left	σ_L	2.41	0.15	0	5	Equation 3
Word length exponent	η	0.448	0.035	0	1	Equation 6
Preprocessing factor	f	70.2	20.6	1	200	Equation 7
Global decay	ω	0.01				Equation 7
Processing noise	φ	2				Equation 9
Saccade timing						
Random timing (ms)	t_{sac}	179.0	3.6	100	250	Equation 13
Inhibition factor	h	2.62	0.15	0	10	Equation 13
Time delay (ms)	τ	375.7	30.0	0	600	Equation 13
Target selection weight	γ	1				Equation 10
Saccade programming						
Labile stage (ms)	τ_{lab}	108.0	1.5	50	150	Figure 4
Nonlabile stage	τ_{nl}^0	6.1	2.7	5	50	Equation 19
Latency modulation	κ_0	105.2	2.7	0	200	Equation 19
Latency modulation	κ_1	0.1				Equation 19

Note. Min = minimum; Max = maximum.

Numerical Simulations

As model input, for all words of the Potsdam Sentence Corpus, word length, word frequency, and predictability were available (Kliegl et al., 2005). The temporal evolution of our model is based on an equation of motion, which is generated as a coupled system of N_w ODEs (Equation 7), where N_w is the number of words in a given sentence. The coupling of the ODEs is given by the saccade dynamics, mainly driven by target selection (Equation 10), and change of lexical processing rates by updating eccentricity after saccades (Equation 2). The ODEs are discretized using the Euler method,[24]

$$a_n(t + \delta t) \approx a_n(t) + (F_n(t)\Lambda_n(t) - \omega)\delta t, \tag{20}$$

where the integration step size is $\delta t = 2$ ms. It is important to note that the noise level of the processing rate (Equation 9) depends on δt, because a different realization for the processing rate is chosen in each time step δt.

Model Parameters

The estimation of model parameters was performed using word-based measures for

- four measures of fixation durations (first fixation duration, second fixation duration, single fixation duration, and total reading time),
- four measures of fixation probabilities (skipping probability, probability for two fixations, probability for three or more fixations, and regression probability); additionally we used
- the distributions of the four measures of fixation durations and
- the relations between fixation duration and within-word fixation position (IOVP effects) for first and single fixation durations.

The details of the fitting procedure are presented in Appendix A. The performance of the model is defined as a sum of mean squared normalized errors of fixation durations and fixation probabilities per word. An optimization procedure was applied to find a set of parameters, which yielded estimates of parameters and errors (see Table 3).

To keep the number of free model parameters as small as possible, we fixed some of the parameters. The noise level of lexical processing was estimated from experimentally observed distributions; $\varphi = 2$ yielded comparable results. Target selection weight $\gamma = 1$ was motivated by Luce's (1959) choice rule and was tested in SWIFT-I (Engbert et al., 2002). The parameter $\kappa_1 = 0.1$ (Equation 19), which represents the range of the latency modulation, was fixed at a reasonable value in advance.[25] We tested a few combinations of fixed values for these parameters in advance, to check the stability of our simulations.

On the basis of the finding that the model is in agreement with experimental data within a certain range of parameter errors, we assume that this error is a plausible value for the simulation of interindividual variance of parameters. In each run, parameter errors were used to simulate interindividual differences. This approach is self-consistent, because parameter uncertainties represent error ranges for parameters, for which the model's dynamics are stable. During the procedure of parameter estimation, the parameter errors converged and settled to specific values indicating the sensitivities of parameters (see also Appendix A). The introduction of parameter errors turns out as a viable solution to the general

[24] Because the temporal evolution of the ODE system is linear during fixations, it is not necessary to apply a more advanced numerical integration method (e.g., 4th-order Runge-Kutta).

[25] The value of $1/\sqrt{2\kappa_1} \approx 2.2$ represents the range of intended saccade length, where the latency modulation is strongest, because κ_1 derives from a Gaussian-type formula.

problem that model results typically show less variance than experimental data.

Simulation Results

We start the discussion of modeling results with an example for a single eye-movement trajectory generated by the model. This example already demonstrates the general mechanism of saccade target selection from the activation field underlying all types of saccades: forward saccades, word skipping, refixations, and regressions. Next, we present examples for word-based measures (four fixation durations and four fixation probabilities), which are computed from 200 runs of the model. These word-based measures were averaged over classes of word frequency and word length in subsequent analyses to evaluate related effects statistically.

After these basic comparisons, we investigate the model's performance on more specific effects. We discuss distributions of initial landing positions, refixation probabilities as a function of landing position, the effect of inverted optimal viewing position of fixation durations and lag and successor effects, and whether our model produces costs for skipping.

Simulation Example

A typical numerical output of the SWIFT-II model is illustrated in Figure 7 by plotting the time evolution of the set of activations $\{a_n(t)\}$ and the fixation position $k(t)$ along the vertical axis. The sequence of words fixated in this example is

$$\{1, 2, 3, 5, 4, 5, 6, 6, 8, 9\}.$$

We now briefly explain some of the phenomena observed in this example.

Word skipping occurs for Word 4 and for Word 7 in first-pass reading. The mechanism for word skipping can be seen clearly in both examples, as we observe parallel activation of several words.

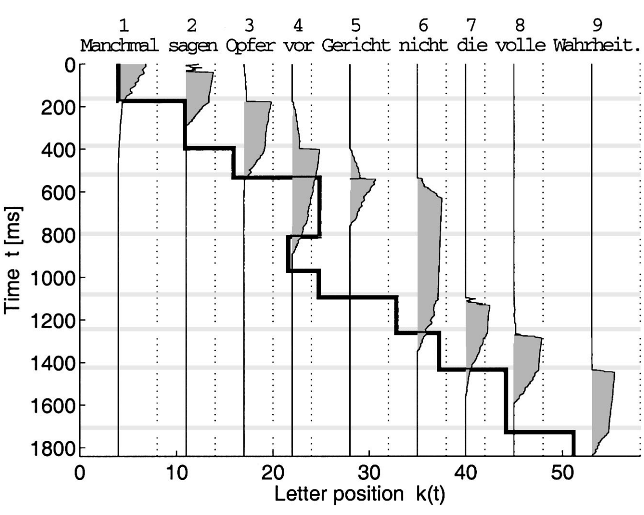

Figure 7. Example of the numerical simulation of the SWIFT model. Time evolves (from top to bottom) along the vertical axis. The fixation position $k(t)$ is indicated by the dark black line in units of letters. Activations $a_n(t)$ are indicated by the gray areas, whereas saccades are indicated by the lighter horizontal lines.

Word skipping is the result of competing activation for target selection. Thus, in our model, words need not to be fully identified in order to be skipped. *Refixations* are likely in difficult or long words or both. In the example shown here, the refixation on Word 6 is the result of a first fixation on the space before Word 6, which is counted as a fixation on the word. As a consequence of this fixation far from the word's center, the activation is still very high when the next saccade target is computed. As a result of the saccade range error and saccadic noise, the second fixation occurs on the last letter of Word 6. Because the realized trajectory in Figure 7 is the result of both target selection and oculomotor processes, it cannot be decided from the plot whether this refixation was "intended" by the model, but of course, we can tell by looking "inside" the model. In the framework of SWIFT, a *regression* can occur because of unfinished lexical access before the corresponding region of text is left. In the example shown here, Word 4 was skipped in the first pass and later fixated with a regression, because parafoveal processing did not lead to full lexical access. Unlike in real data, within the confines of our model we are always in a perfect state of knowledge about the causes and consequences of specific reading patterns.

Word-Based Measures

As the next step toward the statistical evaluation of our model's performance, we analyzed average fixation durations and fixation probabilities for each word. We used 200 runs of the model and calculated averages for four measures of fixation duration and four measures of fixation probabilities, as discussed before.[26] Model simulations were in good agreement with experimental data. Main patterns of fixation durations and fixation probabilities were reproduced at the level of individual words, as illustrated in Figure 8. Deviations for first and last words are due to their exclusion from parameter fitting.

Summary Statistics

To investigate effects of word frequency (CELEX Frequency Norms; Baayen, Piepenbrock, & van Rijn, 1999) and word length, we averaged word-based measures over classes of word frequency (Class 1: 1–10, Class 2: 11–100, Class 3: 101–1,000, Class 4: 1,001–10,000, and Class 5: >10,000; frequencies per million words) and word length (Classes 2 to 11: 2–11, Class 12: ≥12). Figure 9 shows the results for model simulations with the results obtained from experiments. The patterns of fixation durations and fixation probabilities are in good agreement, in particular, our model reproduces the effects of both word length and word frequency correctly. Results on gaze durations are also reported in Appendix D.

Next, we compared the distributions of fixation durations in model simulations with the corresponding distributions observed in experiments. From the agreement between simulated and experimental data (see Figure 10), we concluded that the random-walk process assumption for word processing generates a reasonable amount of variability to reproduce the observed distributions of fixation durations.

[26] These measures were already used in the parameter estimation procedure.

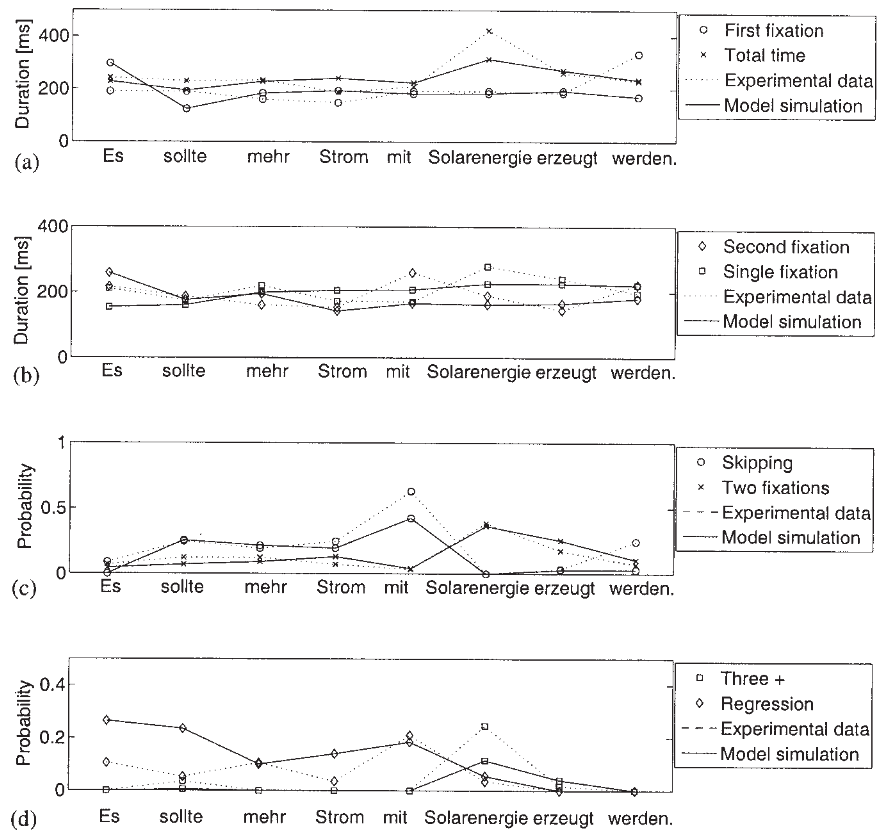

Figure 8. Example of the simulation results on the level of mean values over 200 runs of the model for four different measures of fixation durations (a and b) and four measures of fixation probabilities per word (c and d).

Effects of Word Length and Word Frequency

A well-known problem in assessing the independent contributions of word length and word frequency to visual and lexical processes is the large correlation between the two variables (−.62 for the 850 corpus words used in our simulations, excluding the first and last words of each sentence). In order to investigate effects of word length and word frequency, every sentence of the Potsdam Sentence Corpus contains a target word. These target words are uncorrelated in length and frequency (correlation between word length and log frequency = −.004) and constitute an orthogonal Word Length (3) × Word Frequency (2) design, with 24 words in each cell. Figure 11 displays the results for two duration measures from the word-based summary statistics (see Figure 9), now restricted to target words. For experimental as well as simulated data, each duration measure exhibits both a word length and a frequency effect. For simulated data, however, the frequency effect with longer durations for low-frequency words is considerably smaller than for experimental data. This problem probably reflects the fact that with printed frequency, only one of many other possible lexical variables (such as neighborhood frequency) is explicitly specified in the model.

Initial Landing Positions

Given the general agreement between measures of fixation durations and measures of fixation probabilities at the level of single words and at the level of summary statistics for classes of word length and word frequency, we now compare more detailed aspects related to the oculomotor assumptions in our model. Distributions of initial fixations in words show a rich pattern of variation. Following McConkie et al.'s (1988) study, it is important to analyze corresponding distributions as a function of word length and launch site distance (see Figure 12).

First, model simulations were in good agreement with experimental data. Second, our model simulations reproduced the effects that (a) the standard deviations of distributions of initial landing positions increase with both word length and modulus of launch site distance and (b) the maxima of the distributions are shifted to the end of the words for short saccades (launch site −1) and are shifted to the beginning of words for long saccades (launch sites −5 and −7). Thus, the effects of the implemented saccade range error were clearly visible in the model simulations.

Refixation Probability

Refixations indicate the optimal viewing position in reading, because the minimum of the probability for performing a refixation—as a function of the initial landing position—indicates the best fixation position for processing a word. First, our model includes assumptions on oculomotor control based on McConkie et al.'s (1988) work to produce a realistic variance in initial landing positions. Second, the assumption of a processing gradient turns

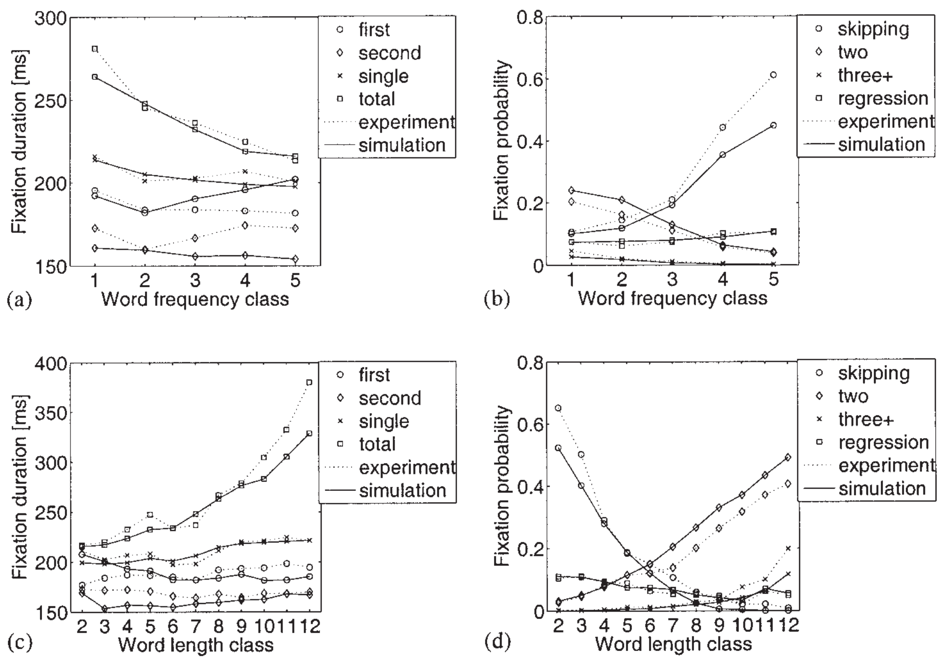

Figure 9. Summary statistics of different eye-movement measures by word-frequency classes and by word-length classes for model simulations and experimental data. (a) Mean durations for first, second, and single fixation durations and total reading time as a function of word-frequency class. Results for model simulations are indicated by the solid lines, whereas results obtained for experimental data are indicated by dotted lines. (b) Probabilities of skipping, of two fixations, of three or more fixations, and that a given word is the target of a regression, as a function of word-frequency class. (c) Mean duration for the same measure as in (a) as a function of word-length class. (d) Probabilities as a function of word-length class.

out to be strong enough to reproduce the U-shaped form of the within-word refixation probability (see Figure 13); however, there was a tendency to a more asymmetric form in the simulations; that is, there are more regressive refixations in experiments. This discrepancy will be explored in future model variants.

It is straightforward to formulate a hypothesis for the function of refixations in long words, as visual acuity decreases strongly from the center of the visual field. Refixations enable readers to process long words using two (or more) fixations by bringing different parts of a word close to the fovea. This interpretation is suggested by experimental data, because we observe the tendency for two fixations at the beginning and end of a word (or vice versa).

For short words (word length less than 5), the function of refixations is less obvious. In our model, we added a new hypothesis to explain refixations independent of effects of word length, because the autonomous saccade generator can induce the start of a new saccade program in the absence of lexical processing demands.

Regression Probability

The results on the probability for interword regressions are of special interest in SWIFT, because of our hypothesis that regressions can be triggered by incomplete word recognition. We expected that it would be rather difficult to reproduce pattern of regressions, if this hypothesis were inadequate. In the summary statistics (see Figure 9), we computed the probability for a word to become the target of a regression. If our hypothesis of incomplete lexical access as a cause of regressions is correct, we would expect a greater regression probability for words that were skipped in first-pass reading. A corresponding analysis for both experimental data and model simulations demonstrates that regression probability is higher for skipped words (see Figure 14). More important, the basic pattern of the experimental data are reproduced by our simulations. Thus, the agreement between experimental data and model simulations supports the hypothesis that incomplete word recognition is a powerful mechanism to explain the pattern of regressions, in particular for effects of word length (see also Vitu & McConkie, 2000). The fact that regression probability is slightly overestimated in our simulations indicates that more constraints are needed to estimate regression probabilities.

Inverted Optimal Viewing Position

Having identified the OVP in reading, we would expect a minimum of lexical processing time for fixations close to the OVP. An analysis of three large corpora by Vitu et al. (2001) demonstrated that this is not the case: Fixation durations are longest, rather than shortest, when the fixation position is at the center of a word. Consequently, this phenomenon was called the *inverted* OVP (or IOVP) effect of fixation durations. A corresponding analysis of data obtained for the Potsdam Sentence Corpus supported the effect (Nuthmann et al., 2005; see also Kliegl et al., 2005).

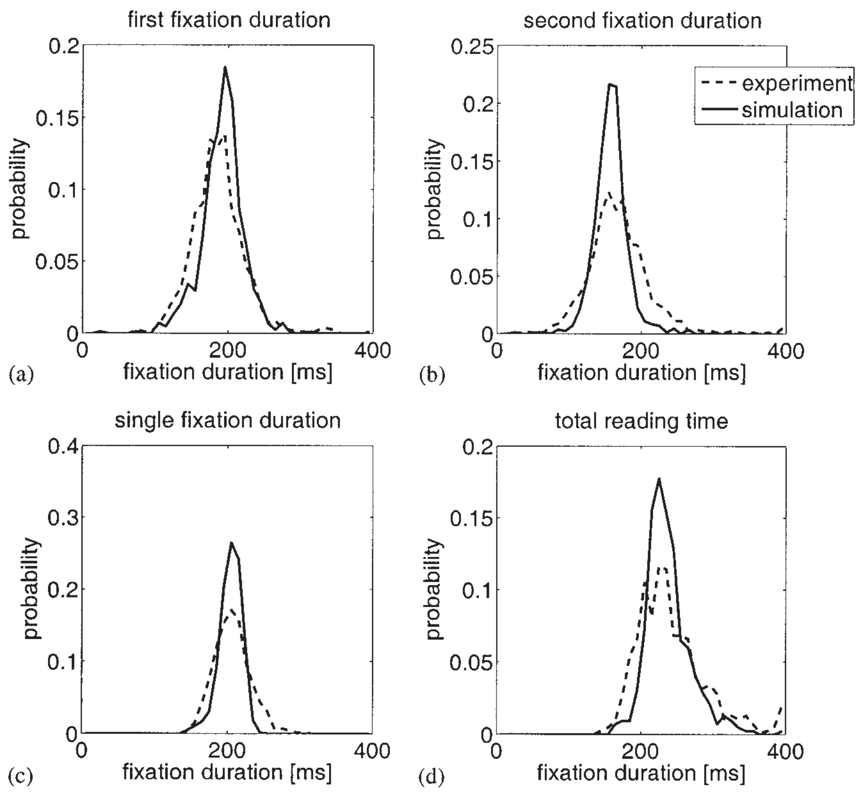

Figure 10. Distributions of fixation durations for experimental data (dotted lines) and model simulations (solid lines): (a) first fixation durations, (b) second fixation durations, (c) single fixation durations, and (d) total reading time.

The IOVP effect for single fixation durations is reproduced by our model (see Figure 15) by implementing Principle 6: error correction of misguided saccades. Near word boundaries for fixation position on the first or last letter of words, the probability for mislocated fixation is higher than close to word centers. If a misguided saccade leads to a fixation on an unintended word, we implemented the immediate start of a new saccade program, which is potentially error correcting. This mechanism induces the de-

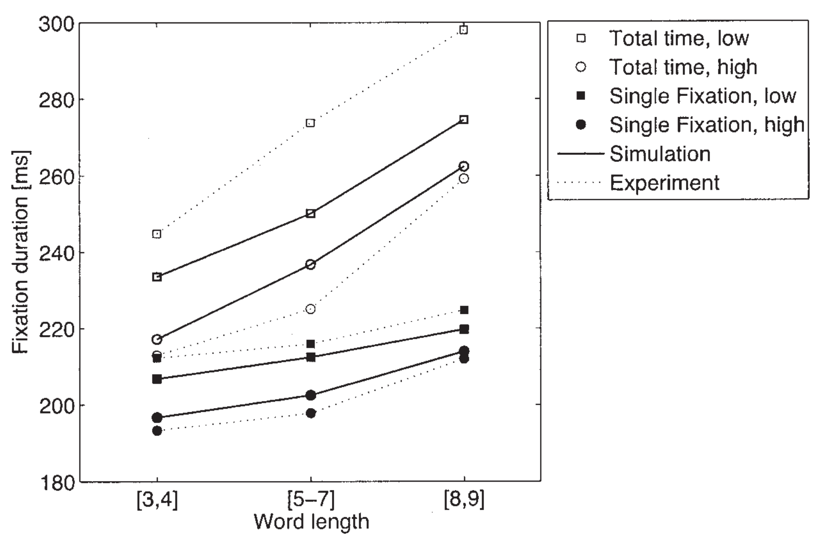

Figure 11. Effects of word length and word frequency in target words. Summary statistics for target words: Mean single fixation duration and total reading time for target words of different lengths (3–4, 5–7, 8–9) and frequencies (high vs. low).

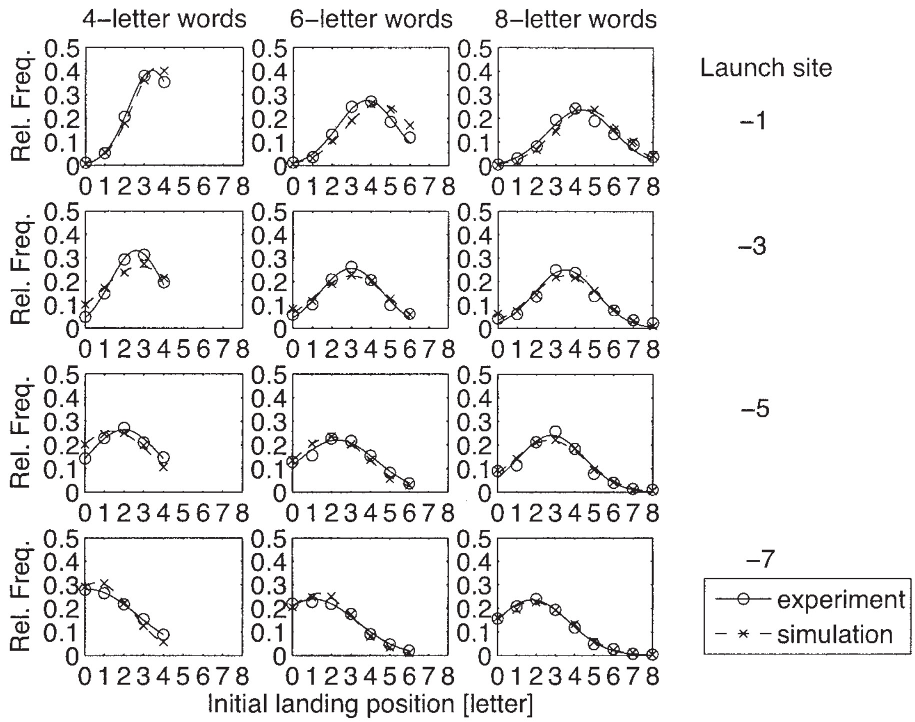

Figure 12. Distributions of initial landing positions by word length and launch site. The rows of panels show distributions for word lengths 4, 6, and 8, and the columns of panels account for launch sites −1, −3, −5, and −7 for saccades. Rel. Freq. = relative frequency.

crease of mean fixation durations near word boundaries, which can explain the IOVP effect. The model reproduced the inverted pattern. Thus, from performance on single fixation durations, we conclude that the proposed error correction mechanism for mislocated fixations is a potential explanation of the IOVP effect.

Although the basic mechanism seems compatible with other models of eye-movement control (e.g., E-Z Reader), we would like to discuss an advantage of the SWIFT model here: There is no need to specify the target of the upcoming new saccade, as saccade target selection is performed by computing probabilities from the activation field, according to the general rule for all saccades (Equation 10). A fixed-target saccade, which needs to be implemented necessarily in E-Z Reader, may be too hardwired, inasmuch as saccade targeting is based on partial knowledge and many saccades may turn out to be no longer required when they start. In the case of mislocated fixations, the intended word may be processed from the parafovea as well and, consequently, an error-correcting saccade is no longer necessary. Therefore, the flexible mechanism in saccade target selection turns out to be an architectural advantage of our model.

For a precise understanding of the mechanism producing the IOVP effect on fixation durations in the model, we performed a

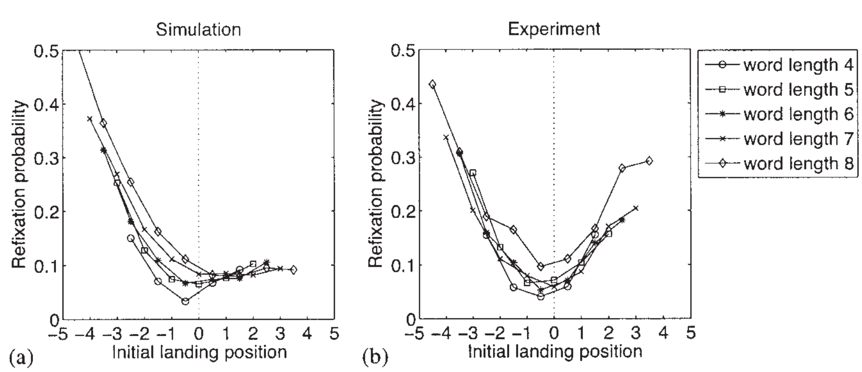

Figure 13. Probability distributions for refixations as a function of the initial landing position. Experimental data (b) show a U-shaped curve without systematic influence of word length. In model simulations (a), the results are reproduced qualitatively.

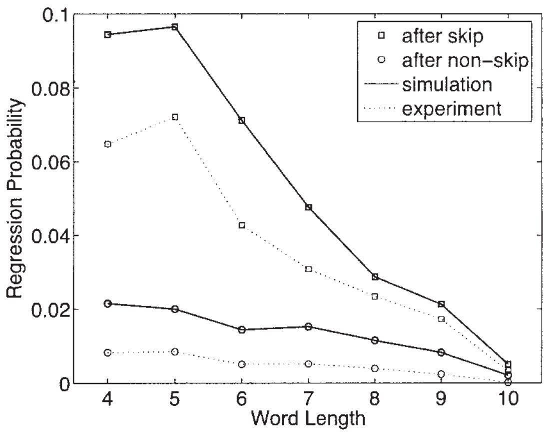

Figure 14. Statistics for interword regressions. Experimental data (dotted lines) demonstrate that regression probability decreases with word length. Moreover, regression probability is much higher for words, which were skipped in first-pass reading. Although the qualitative patterns are reproduced by model simulations (solid lines), regression probability is generally higher in simulations than in experimental data.

detailed analysis of mislocated fixations (Nuthmann et al., 2005). As shown above, our model reproduced the distributions of initial landing positions very precisely. Assuming that the landing distributions (see Figure 16a) can be extrapolated smoothly, we can estimate the probability for mislocated fixations. First, we fit normal distributions to the simulated data. Second, we estimated the overlap of these distributions to neighboring words to obtain the relative fraction (i.e., the probability of mislocated fixations as a function of word length; see Figure 16b). For details of the algorithms see Nuthmann et al. The estimated curves obtained from experimental data (dotted lines) and exact results for the model simulations (solid lines) are in good agreement, which demonstrates that the hypothesis of overlapping distributions of initial landing positions serves as a useful explanation of the IOVP effect in single fixations.[27]

Next, we investigated the IOVP effects in two-fixation cases. The IOVP effect has not been found for gaze durations as a function of initial fixation position, because we observe a trade-off in durations for first and second fixation durations (see Figure 17), so that effects in first and second fixation durations cancel each other.[28] Whereas the IOVP effect is qualitatively the same for first fixation durations as for single fixation durations (Figure 15), average second fixation durations show a U-shaped pattern when plotted as a function of the position of the first fixation. This finding suggests that the amount of processing time spent on the word during the first fixation is saved during the following fixations. Therefore, second fixation durations are shortest near word centers. As an alternative explanation, Vitu et al. (2001) argued that the fixation-duration trade-off effect in two-fixation cases results from the fact that the IOVP effect is found for both first and second fixation durations, combined with the statistical fact that initial fixations near the center of a word (which tend to be longer) are more likely to be followed by a fixation toward one end (which tend to be shorter), and vice versa.

To explain the complicated interaction of first and second fixation durations, we implemented a new mechanism of modulation of saccade latencies as a function of intended saccade lengths (Principle 7) in addition to the principle of error correction of mislocated fixations (Principle 6). For two-fixation cases, error correction could not explain the strength of the inverted U shape of mean first fixation durations. Because the saccade following the first fixation in a two-fixation case has a very short length on average, the nonlabile saccade latency increases strongly because of our assumption in Equation 19. This assumption is physiologically plausible, because the production of a saccade with very small amplitude is a difficult problem for the oculomotor system (Adams et al., 2000; Kalesnykas & Hallett, 1994; Wyman & Steinman, 1973), as an extremely short neuronal pulse must be produced by the brainstem saccade generator (e.g., Sparks, 2002). An additional analysis presented in Appendix B shows that the latency modulation specifically contributes to explain the IOVP effect in first fixation cases, whereas for single fixation durations, the error correction mechanism alone is sufficient to reproduce the inverted U shape of the curve.

Finally, we investigated the influence of word frequency on the IOVP effect. Our analysis is based on corpus target words (see above in section "Effects of Word Length and Word Frequency"). Figure 18 displays results for mean single fixation durations on target words of different lengths and frequency (high [>50 per million] vs. low [1 to 4 per million]) as a function of the landing zone initially fixated. Words of all lengths were divided into five zones (cf. Vitu et al., 2001), and data for each zone were averaged across word lengths and subjects. The empirical data show a frequency effect on fixation durations that was independent of landing zone (Nuthmann et al., 2005; see also Rayner, Sereno, & Raney, 1996; Vitu et al., 2001). The simulated data reproduce this frequency effect qualitatively. The effects of word frequency, however, turned out to be smaller in simulations than in experimental data.

Model Predictions on Current Topics

Whereas the quantitative fits to data are related to well-established experimental findings, we now present model predictions on more recently investigated phenomena. First, we investigate whether our model generates costs for skipping, and second, we analyze lag and successor effects.

Costs for Skipping

The analysis of average fixation durations before skipped words is an interesting test of models of eye-movement control. In general, there are two different processes that potentially contribute to increased fixation durations before skipped words in theoretical models of eye-movement control. First, in models based on SAS, word $n + 1$ is the default saccade target during fixation of word n. As a consequence, word skipping can only occur after a saccade cancelation of the default saccade to word $n + 1$ and the programming of a new saccade to word $n + 2$. Because of the

[27] Note that we validated our algorithm for the estimation of the percentage of mislocated fixation from empirical data by the simulations of our model.

[28] O'Regan and Lévy-Schoen (1987), first reporting a trade-off effect, postulated that a constant amount of time is required for processing a word.

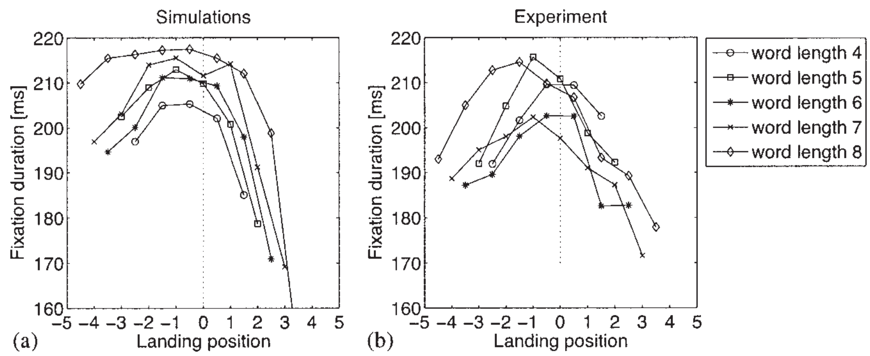

Figure 15. Effect of inverted optimal viewing position for single fixation durations as a function of initial fixation position for model simulations (a) and experimental data (b).

saccade latency and the fact that the cancelation can happen only later than the default saccade to word $n + 1$, there are increased fixation durations before skipped words. Thus, SAS models generically predict skipping costs. The amount of skipping costs, however, might be reduced by the additional assumption of autonomous saccade programs (Engbert & Kliegl, 2001). In SWIFT, word skippings are not causally linked to saccade cancelations because of the general principle of activation-based saccade target selection.[29]

Second, word processing based on GAG will allow parallel processing of words, which implies a longer accumulation of parafoveal information. As a consequence, the probability of skipping word $n + 1$ will increase if the fixation duration on word n increases. Thus, in GAG models, long fixation durations are a cause, not a consequence, of skipping. In these models, however, the link between fixation durations and subsequent skipping is much less tight because there is no strict assumption about default saccade targets as in SAS models. Moreover, in the SWIFT model, saccades are generated autonomously with only a limited modulatory influence from time-delayed foveal inhibition, that is, without triggering by word recognition. In summary, an analysis of skipping costs in SWIFT seems impossible without carrying out numerical simulations.

Experimentally, there have been rather contradictory results on the difference between average fixation durations before skipped and nonskipped words ranging from −26 ms (Radach & Heller, 2000, Table 2) to +84 ms (Pynte, Kennedy, & Ducrot, 2004, Table 3). A solution to this controversy was proposed recently by Kliegl and Engbert (2005) using a statistical analysis that involved pattern matching and a Monte Carlo type of resampling procedure.

In a first step, Kliegl and Engbert (2005) selected three-word segments (triplets) that were read with one fixation per word in forward direction (see Figure 19, top panel: nonskip). For the subsequent statistical analysis, four-word segments were identified that differed from the triplets only by skipping word $n + 1$ (see Figure 19, bottom panel: before-skip). In addition, it was checked that word n was never the target of a regression. To exclude potential influences from within-word fixation position, Kliegl and Engbert matched fixation sequences on word n and fixation zone within word n. To test the differences of fixation durations on word n between patterns, they applied a three-step procedure using 100 Monte Carlo samplings (see Kliegl & Engbert, 2005, for details).

The main results obtained from this analysis were that there were strong effects of word frequency and word length on skipping costs. First, in model simulations (see Figure 20a), there were global skipping costs, that is, average fixation duration was increased before word skipping compared to nonskip cases. The difference curve indicates a linear relation between the increase in fixation duration and the length of the skipped word (Figure 20b). For experimental data, the main results are plotted in Figure 20 (c and d). Fixation durations before short words were shorter when subsequent words were skipped compared with when they were fixated. With increasing word length, this effect is reversed to produce longer fixations before long words. Thus, different from model simulations, there were benefits from skipping short words and costs from skipping long words. As in the model simulations, however, the differences between nonskip and before-skip cases turned out to be roughly linearly increasing with word length (see Kliegl & Engbert, 2005).

In summary, the SWIFT-II model generates global skipping costs, which is in contradiction to our own results from experimental data (Kliegl & Engbert, 2005). Although there are diverging results from different experiments, this might indicate that in the current version of our model, the effects of preview as a consequence of long fixation durations are a dominant process, which causes word skipping. Therefore, it is an open problem whether the model can be modified to generate reduced fixation durations before skippings as well.

Lag and Successor Effects

A key assumption for eye-movement research is that properties of the fixated word are the dominant variables modulating fixation duration. This *immediacy-of-processing assumption* (see Rayner, 1998, for a review) is a platform for much of psycholinguistic research. Using a detailed analysis of a large data basis from continuous reading, we recently showed that there are multiple nonlocal effects of word difficulty (Kliegl et al., 2005).

[29] Saccade cancelations can occur in SWIFT during the labile stage of saccade programming; however, these cancelations do not represent the driving mechanism for word skippings.

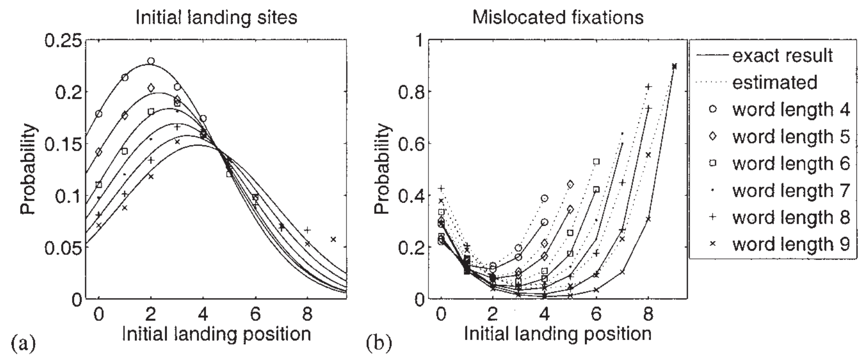

Figure 16. Analysis of mislocated fixations from overlapping initial landing positions. (a) Relative frequency of initial landing positions for different word lengths. (b) The probability of mislocated fixations as a function of letter position for different word lengths. The estimated curves (dotted lines) are calculated from extrapolations of the distributions in (a), whereas the exact results (solid lines) are directly computed from model simulations.

In a sequence of three first-pass single fixations, we computed fixation duration on word n (the center word) as a function of frequencies, predictabilities, and lengths of word $n - 1$, word n, and word $n + 1$ (see Figure 21). A first glance at Figure 21 shows that there are strong effects in both experimental data and model simulations. Most important, however, simulation results generally show the same trend as the experimental data.

Lag effects. The strongest effect (more than 40 ms in average single fixation duration) is produced by the last word's length, which is even stronger than the effect induced by the current word's length (see Figure 21, bottom panels). In the SWIFT-II model, there are two mechanisms that are responsible for this lag effect. First, a fixation on word $n - 1$ will generate less *preview* on word n, when word $n - 1$ is longer. As a consequence, the fixation on word n will last longer on average, if word $n - 1$ was a long word. The same argument also applies to the lag effect for the word-frequency plot (see Figure 21, top panels) because of the correlation between word length and word frequency.

Second, we implemented a time delay in the foveal inhibition process (Equation 13) to account for the neurophysiological fact that the word-recognition loop will operate much more slowly than the fast brainstem saccade generator. The numerical value of the time delay was estimated as $\tau = 375.7$ ms (see Table 3). Given an average single fixation duration of 200 ms, the current word's fixation duration is effectively controlled by inhibition from the last word. Thus, the time-delayed foveal inhibition will produce spillover effects.

Successor effects. The performance of our model with respect to successor effects (i.e., effects of the features of the successor word $n + 1$ on fixation durations of word n) is rather interesting, because there are no explicit mechanisms for modulations of foveal processing by processing of words to the right of the currently fixated word. As a consequence, all effects in Figure 21 are effects due to spatial selections in the perceptual span. A note of caution: Successor effects are small compared with the lag effects in both experimental and simulated data (Kliegl et al., 2005). Thus, future model modifications might change the data

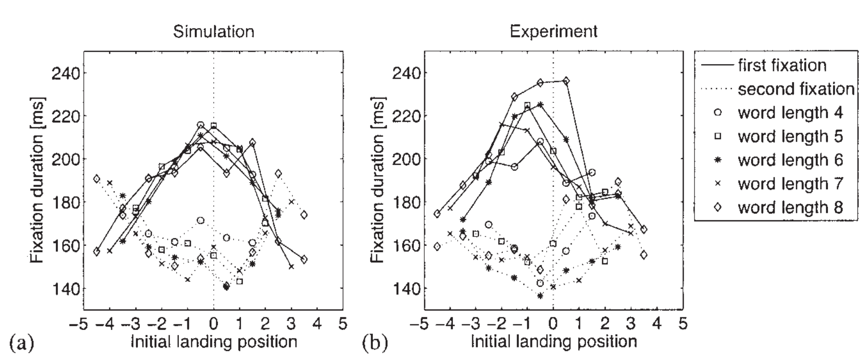

Figure 17. Effects of optimal viewing position on fixation durations of two-fixation cases. In the experimental data (b), there is a clear trade-off effect between first and second fixation durations, with a pronounced U-shaped curve for second fixation durations as a function of the position of the first fixation. In the results from the numerical simulations (a), the model reproduced the U-shaped curve for second fixation durations, whereas the inverted optimal viewing position effect for first fixation durations was less pronounced than in the experimental data.

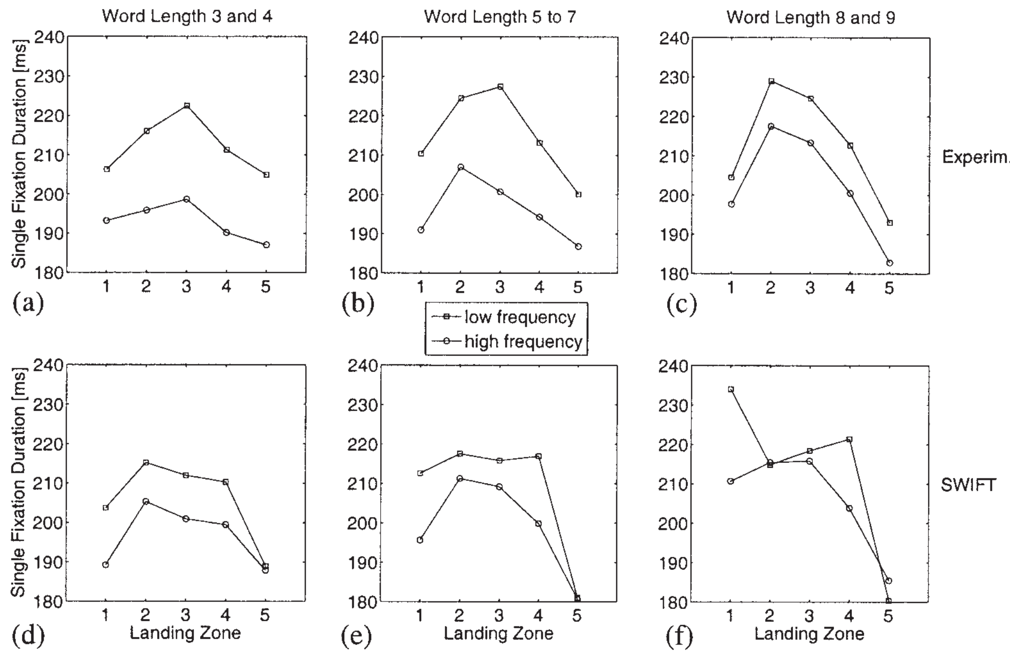

Figure 18. Inverted optimal viewing position curves as a function of word frequency, for experimental data (first row) and model simulations (second row). Displayed are mean single fixation durations on target words of different lengths (3 and 4; 5–7; and 8 and 9) and frequencies (high vs. low) as a function of the landing zone initially fixated. Words of all lengths were divided into five zones, and data for each zone were averaged across word lengths and subjects.

pattern on successor effects more strongly than other effects. We report the predictions about successor effects to stimulate future research.

Is Word Processing Parallel or Serial?

In the SWIFT model, all words are processed in parallel because of the assumption of a processing gradient. The processing rate, however, decreases very rapidly with increasing eccentricity. Thus, the number of words with effectively changing activations is much smaller than the number of words N_w in a sentence. A dynamical analysis shows that SWIFT's behavior can be investigated qualitatively by the activations of only three words, $a_k(t)$, $a_{k+1}(t)$, and $a_{k+2}(t)$, during fixation of word k. In terms of dynamical systems theory (e.g., Kaplan & Glass, 1995), we can show that the dynamics of SWIFT can be approximated by a two-dimensional subspace embedded in an N_w-dimensional state space (see Appendix C). Therefore, the potential number of dynamical degrees of freedom are reduced by the estimated model parameters values in a psychologically plausible way, so that only a few activated words determine SWIFT's behavior at a time.

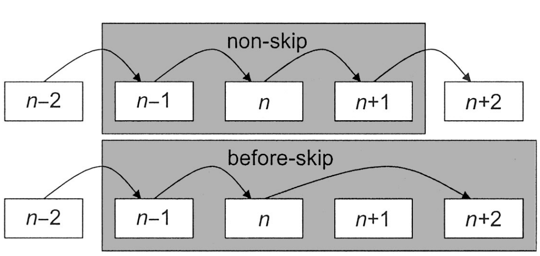

Figure 19. Pattern selection for the analysis of skipping costs. For comparing fixation durations, matched fixation sequences for nonskip cases (top panel) and before-skip cases (bottom panel) were selected.

The two alternative theoretical concepts of serial (SAS; e.g., Engbert & Kliegl, 2001; Reichle et al., 2003) versus parallel (SWIFT) processing of words are asymmetrically related to each other with respect to generalization. Whereas serial processing may be looked upon as a special case of a model of parallel processing, new assumptions must be made in a serial model to extend the model to parallel processing. On the basis of these considerations, we introduce a parametrization for a continuous tuning of the SWIFT model from strictly serial to parallel processing. Thus, the distinction between serial and parallel processing is not necessarily dichotomous, and we can study both processing types within the same model.

Given the gradient-type assumption of parallel processing of words, we can add restrictions on parallel processing to include serial processing as a special case in SWIFT's behavior. Because word recognition is a two-stage process in SWIFT, there are two different versions of the serial model: Model A, in which global processing (preprocessing and lexical completion) is serial, and Model B, in which lexical completion is serial and preprocessing is parallel.

For both Versions (Models A and B) of serial versus parallel processing, we can define a parametrization, which introduces a continuous transition between serial and parallel processing by tuning a single parameter ϕ. The basic assumption is that processing is modulated by the number of words with nonvanishing activation to

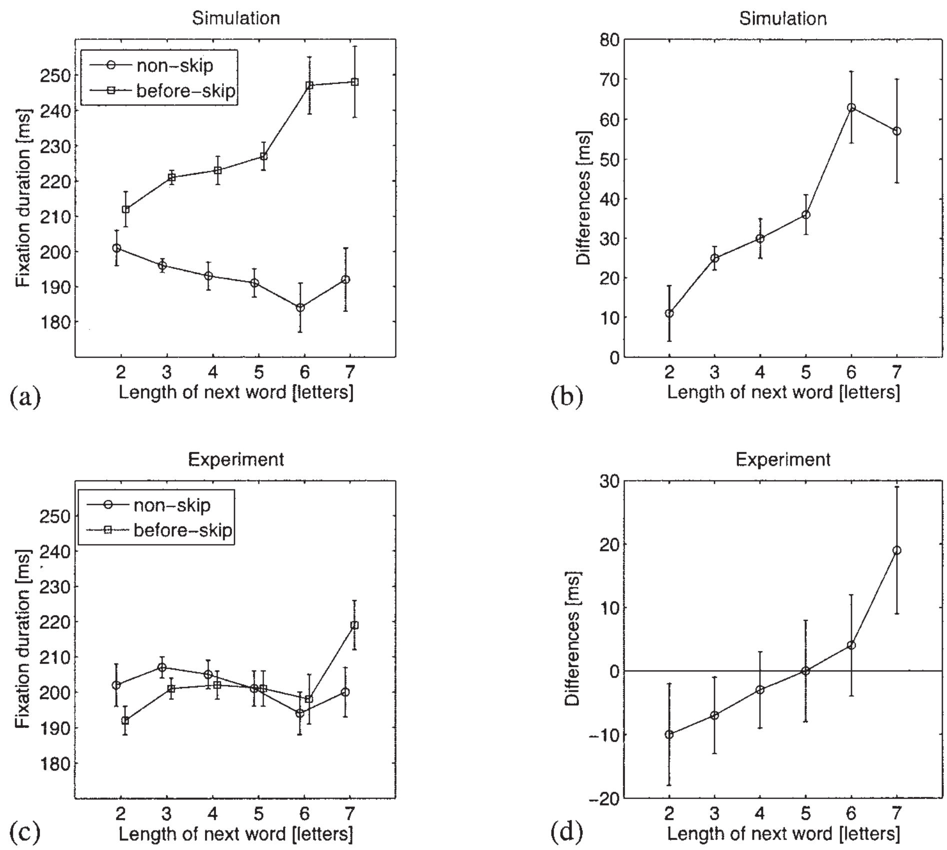

Figure 20. Analysis of costs for word skipping from statistical analysis. Model simulations: (a) Fixation durations increase with word length (of the skipped word) before a skip and slightly decrease with word length before a nonskip. There are global costs. (b) The differences between cases of skips and nonskips increase approximately linearly with word length. Experimental data: (c) There are reduced fixation durations before short skipped words and costs before longer skipped words compared with nonskipped cases. (d) The difference increases linearly with the length of the skipped word.

the left of the word under consideration, because any word with nonzero activation signals that the corresponding word is not completely identified. To formulate this approach mathematically, we replace the processing rate $\lambda_n(t)$ of word n (Equation 6) by

$$\lambda_n^{\phi}(t) = \left(\frac{1}{P(t)}\right)^{\phi} \lambda_n(t), \tag{21}$$

where $P(t)$ is the number of words with nonzero activation $a_m(t) > 0$ at time t, from word 1 up to word n (i.e., with $m \leq n$). As a consequence, the processing rate $\lambda_n^{\phi}(t)$ of word n is decreased for increasing numbers of words to the left of word n. More important, both serial and parallel processing are included in Equation 21 if we consider the two limiting cases:

$\phi \rightarrow 0$: parallel processing

$\phi \rightarrow \infty$: serial processing.

Obviously, for $\phi \rightarrow \infty$, processing of word n is prevented if $P(t) > 0$.

To implement the two different versions (Models A and B) of serial processing introduced above, we apply Equation 21 to preprocessing and lexical completion (Model A, in which processing of words is controlled by parameter $\phi \equiv \phi_A$) or to the lexical completion process only (Model B). In the latter case, preprocessing will lead to a parallel activation of words, whereas the decrease of activations during lexical completion will vary between parallel and serial processing depending on parameter $\phi \equiv \phi_B$.

Next, we demonstrate by numerical simulations that variation of parameter ϕ can induce the transition from parallel to serial processing. Using 100 runs of the model, we computed the fraction of time Λ_j (from total simulation time), where j words have nonzero activation. In a strictly serial model, the fraction Λ_j must be zero for $j \geq 2$; that is, there is maximally one activated word at a time.[30] It turns out that in SWIFT, $\Lambda_1 = 19\%$, $\Lambda_2 = 32\%$, and $\Lambda_{>2} = 48\%$. Thus, there are more than two words with nonvanishing activation for nearly 50% of the time. Keeping all parameters of the SWIFT model fixed, we vary parameter ϕ for both Versions A (with $\phi \equiv \phi_A$) and B (with $\phi \equiv$

[30] For an efficient model, we would also require that Λ_0 be close to zero, because during the time interval with vanishing activation for all words, nothing is processed.

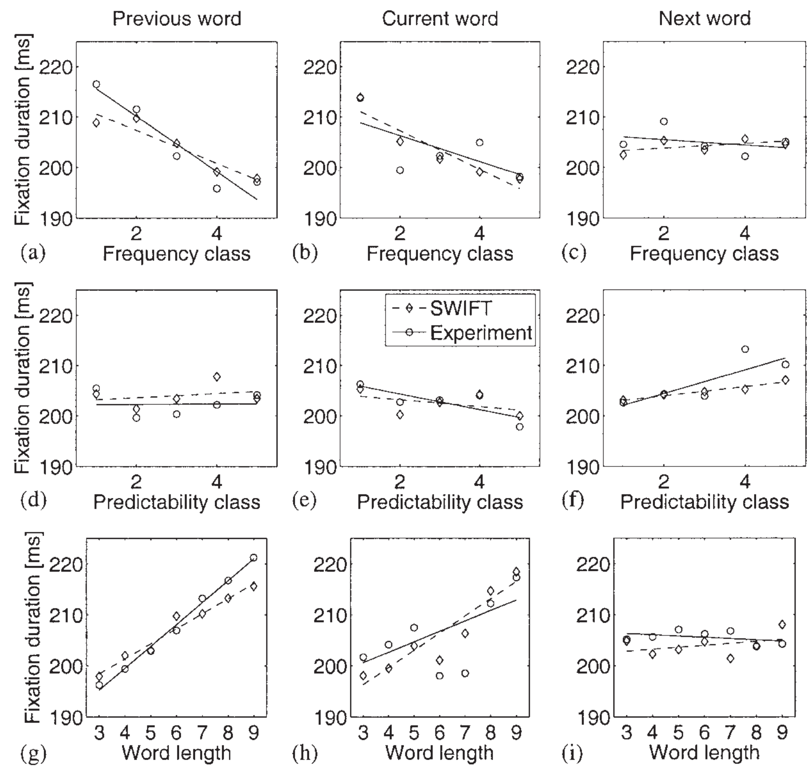

Figure 21. Analysis of lag and successor effects. Bottom row: Average single fixation durations as a function of word length of the previous word (word $n - 1$, left column), the current word (word n, middle column), and the next word (word $n + 1$, right column). Middle and top rows: Corresponding plots as a function of word-predictability class and word-frequency class, respectively.

ϕ_B) and compute the resulting fractions Λ_j (see Figure 22). The SWIFT model is retained for $\phi = 0$, but our simulations show that the model's behavior will be rather stable up to $\phi \approx 0.1$.

If processing rates are modified by Equation 21 for both preprocessing and lexical completion (Model A), we observe a sharp transition from parallel to serial processing, which is indicated by the rise of Λ_1 close to 100% at $\phi \approx 10$ (note that the direction of the abscissa is inverted; i.e., ϕ increases from right to left in Figure 22a). If we restrict the lexical completion stage of word processing only (Model B), the distribution of activations changes less drastically (see Figure 22b). It is interesting that the fraction of time with one activated word, Λ_1, decreases with increasing ϕ. Therefore, if lexical completion becomes more serial, the distribution of activation will be broader. This effect is caused by the fact that there are no restrictions on preprocessing: Several words are preprocessed at a time, but the model must wait to start lexical completion until all words to the left of the word under consideration are completely identified.

Because we demonstrated that the SWIFT model can be used as a framework to study the transition from parallel to serial processing, it may be an important tool to generate predictions on a number of phenomena, which are currently investigated to determine experimental boundary conditions on the possibility of parallel processing and on the limitations of serial processing. In this respect, two candidate phenomena are the analysis of skipping costs and lag and successor effects discussed in the previous section.

General Discussion

In this article, we developed an advanced and substantially extended SWIFT-II model based on the first version, SWIFT-I (Engbert et al., 2002). An incremental study of the effect of adding the various mechanisms to the basic framework is carried out in Appendix B. We showed that the new model can reproduce and explain many experimentally observed phenomena of eye movements during reading. Whereas the model's intended level of mathematical detail with respect to word processing and saccade programming agrees with the E-Z Reader framework (Reichle et al., 1998, 2003), the core assumption of spatially distributed processing in SWIFT turned out as a viable alternative to the strictly serial allocation of attention assumed in E-Z Reader.

Motivated by recent advances in the dynamic field theory of movement preparation (Erlhagen & Schöner, 2002), we implemented SWIFT as a computational model for saccade generation based on a spatially distributed activation field. There is similarity of the SWIFT model with the dynamic field concept; however, we did not refer to the formal theory of Erlhagen and Schöner. The main reason was that saccade generation in reading is not only a problem of movement planning, but also a problem of word processing, so that many properties related to word processing had to be combined with ideas proposed in the dynamic field theory. Thus, the dynamic field concept motivated our model, but the formal framework was simplified in order to focus on aspects of word recognition in order to reproduce effects of word difficulty in

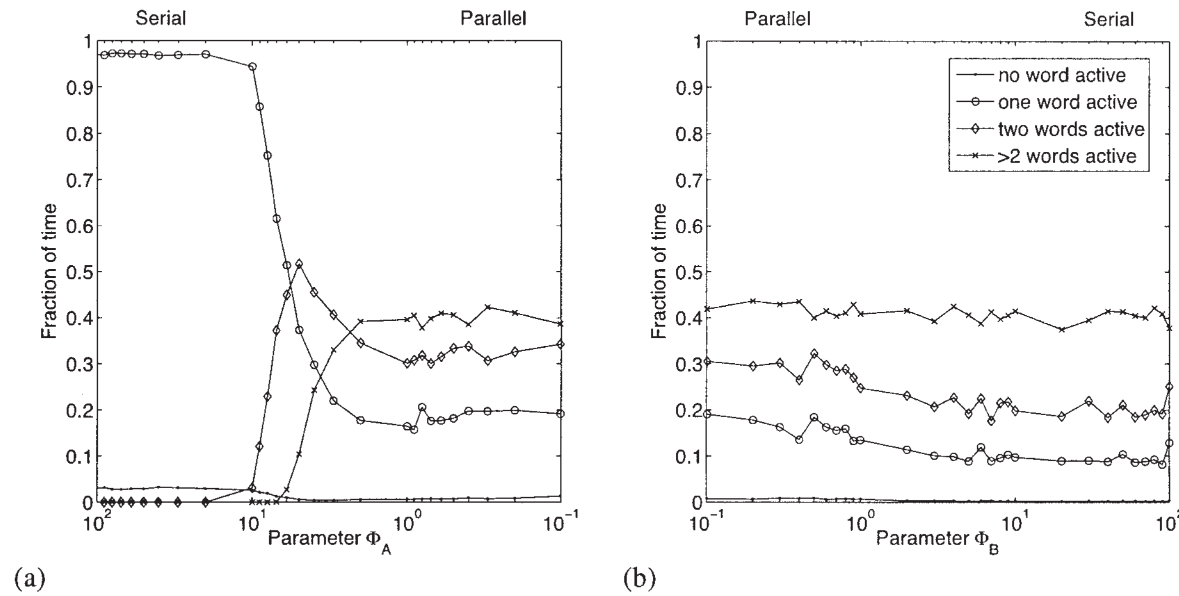

Figure 22. The transition from parallel to serial processing in the SWIFT model. (a) If the processing rate is controlled by parameter ϕ for both preprocessing and lexical completion (Model A), then we observe a sharp transition to serial processing $\Lambda_1 \approx 100\%$ for $\phi \approx 10$. (b) When lexical completion is modulated by ϕ with preprocessing fully parallel (Model B), the distribution of activation over words is even broader than in the SWIFT model.

eye-movement data. In perspective, we believe, however, that the general concept of interactions between local excitation and global inhibition in the dynamic field theory is a potentially very useful framework for a coherent explanation of eye movements during reading.

Neurophysiological Background

The investigation of the brainstem circuitry of saccade generation has been an active field of research for many years, resulting in a very detailed level of understanding of the immediate presaccadic processes (Moschovakis, Scudder, & Highstein, 1996; Sparks, 2002). One of the key results is that there exist both omnipause and burst cells in the brainstem. Whereas omnipause cells fire during fixations and cease activation during saccades, the burst cells show the opposite activity pattern; that is, burst cells fire at a high rate for the duration of a saccade. Because omnipause cells show no specificity, but burst cells code the spatial metrics of saccade, there are at least two descending pathways in the neurophysiology of the oculomotor system. One carries spatial information (“where”), whereas the other serves as a trigger and is involved in temporal aspects of saccades (“when”).[31] The competing processes between fixation and saccade generation have been further investigated by Munoz and Wurtz in a series of publications (Munoz & Wurtz, 1993a, 1993b, 1995a, 1995b; Wurtz, 1996). Their work has focused on the superior colliculus, which carries a representation of the fovea of the visual field. The superior colliculus shows distributed coding as an important property (McIlwain, 1991). Visual cells turned out to have unexpectedly large receptive fields. Thus, a cell in the collicular map can be activated from a rather wide range of visual space. Motivated by these neurophysiological results, Findlay and Walker (1999) proposed a general model for the control of eye movements. The model is organized into five different levels, all of which are separated into “where” and “when” pathways. Moreover, Findlay and Walker suggested that processes of competitive interaction operate within a salience map (their Level 2) to compute a unique saccade goal.

In the SWIFT model, we adopted the fundamental separation between “where” and “when” pathways as a key principle of model design. As a consequence, we implemented temporal and spatial control of saccades with as little interaction as possible. It turned out in the development of SWIFT-I (Engbert et al., 2002) that foveal inhibition of an autonomous random timer is a minimal model of the control processes necessary to adjust fixation durations. Here, we included a time delay for the inhibition process to separate the slower word-recognition system from the fast brainstem saccade generator. Given the neurophysiological organization of the contributing neural systems, the time-scale separation is very plausible. The competition between alternative saccade targets is a powerful mechanism for generating all types of saccades (forward saccade, word skipping, refixations, regressions) from a single underlying mechanism. Therefore, the neurophysiological foundations of saccade generation in reading are compatible with our mathematical model.

[31] The concept of separate “where” and “when” pathways was first introduced by oculomotor physiologists (Van Gisbergen, Gielen, Cox, Bruijns, & Kleine Schaars, 1981).

Phenomena Reproduced by SWIFT

Word-based measures. Using experimental data obtained for the Potsdam Sentence Corpus (Kliegl et al., 2005), we fitted word-based fixation durations and probabilities. For all of the 850 words of the corpus (all words of the corpus excluding first and last words of the sentences), the model reproduced averages of first, second, single, and total fixation durations as well as probabilities for skipping, two fixations, three or more fixations, and regressions. Word-based fitting is a major advantage compared with fitting averages representing classes of word frequency, as was done in previous studies (Engbert & Kliegl, 2001; Engbert et al., 2002; Reichle et al., 1998, 2003), because word-based analyses provide a new level of detail for analyses of model performance.

Effects of length and frequency. The obtained word-based measures are the basis for additional analyses of effects of both word length and word frequency by averaging dependent variables over classes of length and frequency, respectively. This analysis demonstrated that SWIFT accurately captures effects of both word length and word frequency. Thus, SWIFT is the first computational model that reproduces effects of word length and word frequency to a comparable level of accuracy.

Distributions of fixation durations. Fixation durations in reading are highly variable and show broad distributions. Therefore, it is important that computational models reproduce these distributions. There are two main sources of variability for fixation durations in SWIFT. First, the standard deviations of fixation durations are modulated by the stochastic assumptions on the random-walk process for word recognition. This simple assumption can be replaced in a future version of our model without changing the model's architecture. Furthermore, foveal inhibition can influence the variability of fixation durations in a more complicated way (compared with the random-walk process). As an example, a broad distribution of fixation durations will induce a broader distribution of the variability created by foveal inhibition and, hence, amplify the noise. Such complicated interactions of stochasticity and nonlinearity typically occur in nonlinear dynamical systems (e.g., Millonas, 1996; Moss & McClintock, 1989).

Refixations. The within-word position of the minimum of the probability for refixating a word defines the optimal viewing position. In SWIFT, refixations on short words occur as a consequence of autonomous saccade timing. For longer words, refixations are necessary because of visual acuity limitations, which are incorporated in SWIFT by the assumption of the processing gradient.

Regressions. Liversedge and Findlay (2000) put the mechanisms underlying regressive saccades on the list of outstanding problems in eye-movement research. In normal reading, regressions are the rule rather than the exception. Following Rayner (1998), 10% to 15% of all saccades are regressive. As a consequence, for a typical sentence of eight words, the probability for a regression is about 2/3 (ranging from .57 to .73).[32] In SWIFT, regressions are triggered by incomplete word recognition. This is a simple and psychologically plausible explanation, which is supported by our analysis of patterns of words that were targeted by a regression after skipping during first-pass reading.

Initial landing positions. Following the hypothesis first proposed by McConkie et al. (1988) that oculomotor errors can be divided into systematic and random components, we included these two types of saccadic errors in our model. Our simulations show that the distributions of experimentally observed initial landing positions are reproduced by the model. This is a nontrivial result, because it proves that the assumptions on oculomotor control made in SWIFT are compatible with the error pattern found by McConkie et al.

IOVP effects and mislocated fixations. The presence of oculomotor errors induces mislocated fixations (Nuthmann et al., 2005). It is likely that the cognitive control system responds to these errors with some correction mechanism. Such a mechanism represents a coupling of word processing and oculomotor systems. Computational models are ideal tools to test the hypothesis on the consequences of mislocated fixations. In SWIFT, we implemented an error-correction program as a response to mislocated fixations, as proposed earlier by Nuthmann et al. Because mislocated fixations are more frequent near word boundaries, the immediate triggering of a new saccade program reduced fixation duration at word edges. Therefore, our model can explain IOVP effects. An additional modulation of saccade program duration by intended saccade length was used to reproduce IOVP for the first of two fixations.

Costs for skipping. The SWIFT model reproduces the main features of data pattern in skipping costs. From a careful analysis of experiments, Kliegl and Engbert (2005) reported skipping benefits for short words and skipping costs for long words, respectively: Fixations prior to skipped words were shorter for short or high-frequency words and longer for long or low-frequency words compared with nonskipped controls. These results were not reproduced by our simulations, which indicated global skipping costs; however, the model could reproduce a linear increase of skipping costs with the length of the skipped word, which was found in experimental data.

Lag effects. Nonlocal effects of word properties (e.g., word length and word frequency) are not surprising in a model of spatially distributed processing. We checked two effects to investigate whether SWIFT makes realistic predictions about these effects. The lag effect, the influence of the word length and word frequency of the previously fixated word on the currently fixated word, is reproduced qualitatively by two underlying mechanisms in SWIFT. First, when the previous word is a long word, there has been less preview on the current word than in the case of a short successor word, which will lead to an increase in fixation duration. Second, foveal inhibition is time delayed, so that the word recognition loop can modulate fixation duration only with a time delay.

Further problems. There were and still are numerous data patterns hidden in the Potsdam Sentence Corpus that challenged the model and will continue to do so. For example, in its current version, the model still tends to overestimate the effect of word length and to underestimate the effect of word frequency (see Figures 11 and 18). We also had considered it plausible that lag effects should be found in SWIFT simulations once we had discovered the pattern in the experimental data. Unfortunately, this was not the case for the simulation results. The solution was to delay the inhibition of saccade programs by foveal activation (see Equation 13). It is a physiologically highly plausible generalization

[32] Sentences with regressions are regularly excluded from modeling in E-Z Reader.

of our foveal inhibition mechanism to introduce a time delay for the control of fixation durations by word-recognition processes. Moreover, this modification of the model did not interfere with other successful simulation results despite the nonlinearities in the model. The bottom line is that obviously the model can still be falsified by experimental data, probably in many ways. And, of course, we will look for modifications that accommodate these results without compromising the core set of theoretical principles.

From Parallel to Serial Processing of Words

In SWIFT, several words are active at a time and lexical completion of words is not strictly tied to their serial order in the sentences. This is sometimes advanced as an argument against parallel models, because in SAS models, words become available in the order of appearance in the text, just like in spoken language. Of course, we could simply “delegate” the task of serialization in SWIFT to higher order structures such as Baddeley’s (2000) episodic buffer or Ericsson and Kintsch’s (1995) long-term working memory. Indeed, experimental results about failures to notice missing function words or to overlook their repetition suggest that reading may not be as strictly serial as envisioned by SAS proponents. Koriat, Greenberg, and Kreiner (2002) argued that, for example, function words such as *the* become available earlier and serve to generate a sentence structure into which meanings of content words are then integrated (see also Kennedy, 2000a, for a collection of arguments why reading is not like listening; Deubel, O’Regan, & Radach, 2000; Inhoff, Radach, Starr, & Greenberg, 2000). The failures associated with function words mentioned above are assumed to arise from a faster decay of activation compared with content words (conceptually compatible with SWIFT).

There is good evidence that silent reading activates phonological representations (e.g., Pollatsek, Lesch, Morris, & Rayner, 1992; Van Orden, 1987). At first glance this may even appear to support the assumption of sequential lexical access, as enforced, for example, in E-Z Reader. We note, however, that oral reading is characterized by a strikingly unserial sequence of fixations, with the eye running ahead of the voice, but also frequent regressions to briefly synchronize voice and eye (Buswell, 1920). Oral reading behavior appears to be in better agreement with SWIFT’s assumptions. Modeling such dynamics of eye and voice will provide new constraints for the coupling between ocular and attentional movements; it certainly represents a challenge of generalizability for computational models of silent reading such as SWIFT and E-Z Reader.

Finally, at the other end of conscious control during reading, mindless reading constitutes evidence prima facie for a loose coupling between ocular and attentional control (Rayner & Fischer, 1996; Vitu, O’Regan, Inhoff, & Topolski, 1995). Readers frequently find themselves at a location in the text without any awareness about how they got there or any awareness about what they just read. Clearly, in this situation their thoughts strayed off the text and accessed “meanings” different from the ones written about in the text. We think this situation is analogous to the experience of walking while carrying out an intensive conversation. One’s movements are clearly guided by environmental cues but there is little awareness of this behavior. The two systems must be coupled at some level, but, in our opinion, a strict coupling is not very plausible.

A conceptual advantage of SWIFT as a parallel model of word processing is that we can include serial processing as a special case. Furthermore, by implementing a tuning parameter, we showed that the dichotomy of serial versus parallel processing can be replaced by a continuum of models. There are two different versions of the restriction to serial processing. In the first version, we restricted all processing (i.e., preprocessing and lexical completion), whereas in the second version, we restricted lexical completion only (i.e., preprocessing is still fully parallel). For the first version, we were able to demonstrate by numerical simulations that SWIFT can be restricted to process words serially. A signature of strictly serial processing was that there is only one word activated at a time. In the second version, based on the relaxed assumption on serial processing that preprocessing is still parallel but lexical completion is serial, we showed that the distribution of activations over words was even broader than in the original model. Thus, the SWIFT model may prove to be very useful to further explore the transition from serial to parallel processing in future research.

Comparison With the E-Z Reader Model

A possible classification of models of eye-movement control in reading categorizes the approaches into POC, models based on the principle of GAG, and models driven by SAS. Several computational models have been developed in each of the three categories. Because most models focus only on a very special aspect of eye-movement control (e.g., oculomotor theories do not account for effects of word frequency) or have not been implemented on a computer to generate data for quantitative evaluation, we will compare the SWIFT-II model as a viable implementation of GAG with the E-Z Reader model in its latest version (Reichle et al., 2003) as the most advanced model of SAS. Both SWIFT and E-Z Reader reproduce a comparable number of experimentally observed phenomena, but are based on very different principles, parallel word processing in SWIFT and serial word processing in E-Z Reader. We point out, however, that we adopted a few of E-Z Reader’s principles: that lexical difficulty is related to word frequency and predictability, the concept of two-stage lexical processing, and the two-level programming of saccades. Moreover, both models adopted the concept of systematic and random errors of saccades (McConkie et al., 1988).

The evaluation of different theoretical explanations is among the central problems of research, in particular in mathematical modeling of experimental data (e.g., Myung, Forster, & Browne, 2000). To guide the evaluation and comparison of different models, a number of criteria were proposed by Jacobs and Grainger (1994). Here we discuss the following criteria: (a) plausibility, (b) interpretability, (c) generalizability, and (d) complexity. Note that the relative importance of these criteria might depend strongly on the types of models discussed and the research field.

(a) Plausibility and explanatory adequacy. To check the plausibility and explanatory adequacy of the models, we ask whether the theoretical explanation the models offer are biologi-

cally and psychologically plausible and consistent with the knowledge in the corresponding field of research.

The E-Z Reader model is motivated by SAS driving eye movements in reading.[33] The mechanism of SAS was introduced first by Morrison (1984), motivated by the attentional "spotlight" metaphor from attentional cuing experiments (Posner, 1980). Basic research on the relation between attention shifts and saccade programming resulted in the observation that attentional shifts precede saccades obligatorily (e.g., Deubel & Schneider, 1996; Kowler et al., 1995). In the E-Z Reader model, however, the basic mechanism for starting a saccade program is a preliminary stage of word processing called the *familiarity check.* Thus, the attentional shift occurs *after* the start of the eye-movement program. In an analysis of the E-Z Reader model, Deubel et al. (2000, p. 357) argued that "the assumption that saccades can be programmed without an obligatory, preceding shift of attention is certainly in conflict with most of the more recent investigations on the relation of attention and saccade control." From these considerations, one of the basic assumptions of the E-Z Reader model seems questionable.

An alternative view on the role of attention shifts for eye-movement control during reading has been discussed recently (Reichle, Pollatsek, & Rayner, in press). According to these arguments, visual processing is not sufficient for word identification, which requires, in addition, that attention be focused on the word. This hypothesis is based on findings that attention is essential for "binding" together features of visual objects for encoding single, unified representations (Treisman & Gelade, 1980; Treisman & Souther, 1986; Wheeler & Treisman, 2002; Wolfe, 1994; Wolfe & Bennett, 1996). From this line of evidence, Reichle et al. (in press) further argued that attention must be allocated to each word "object" so that it can be identified. Obviously, the role of these processes for word recognition in a continuous task such as reading, in particular with respect to the time lines involved for attention shifts, remains an open research problem.

The separation into "where" and "when" pathways for spatial and temporal control of saccade programs, respectively, is one of the key findings in basic research about the oculomotor system (e.g., Wurtz, 1996). The SWIFT model is built around this principle, requiring a dynamically changing activation field for saccade target selection (dynamic field theory; Erlhagen & Schöner, 2002, see below). Using this concept, the allocation of visual attention is specified by a gradient function in the SWIFT model. Furthermore, there is no direct coupling between attentional and oculomotor systems, inasmuch as attention is not necessarily word-based in SWIFT. Thus, the time course of attentional shifts in E-Z Reader is in contrast with the less explicit Gaussian-distributed attention in SWIFT.

(b) Interpretability. Both SWIFT and E-Z Reader have a number of parameters that can be interpreted psychologically and/or neurophysiologically. As a consequence, these models are ideal tools for testing alternative assumptions through the evaluation of obtained parameter values. As an example, we fit the labile and nonlabile saccade latency parameters to check whether the numerical values obtained by parameter estimation are plausible. It turned out that the corresponding values are in good agreement with results from basic oculomotor research. We suspect that such a test would be very interesting for the E-Z Reader model, as the SAS mechanisms might exert strong constraints on the durations of saccade program stages.

(c) Generalizability. When we consider visual tasks different from reading, many of the involved cognitive and oculomotor subsystems overlap or are even the same. Whereas the tremendous variability of stimuli in general scene perception currently precludes a fully quantitative approach for models of eye-movement control, visual search tasks that include eye movements (e.g., Gilchrist & Harvey, 2000; Hooge & Erkelens, 1998) are good candidate paradigms for extending and/or generalizing mathematical models.

The most important complication is that in a visual search task, eye movements must be controlled in two dimensions. Reading, however, is effectively a one-dimensional task, because return sweeps from one line of text to the next are not dominating the reading process. Using the concept of an evolving activation field in combination with Gaussian-distributed attention, it is straightforward to generalize the SWIFT model to two-dimensional tasks (for a visual search task see Trukenbrod & Engbert, 2005). In E-Z Reader, attention must be directed to the next item by a random process, because simultaneous preprocessing of several items is prohibited in the SAS framework. Whereas we speculate that there might be an advantage for the SWIFT model, the details of how computational models of eye-movement control perform in visual search tasks involving eye movements must be worked out in future research, of course.

(d) Complexity. A general principle in the design of mathematical models is to keep the model's complexity low. There is, however, no general theory of complexity or even of model complexity (see Badii & Politi, 1997).[34] Although an analysis of model complexity might unveil new insights into the underlying principles of the models, currently it does not seem appropriate to compare models quantitatively using concepts of complexity.

The SWIFT model generates all types of saccades within a coherent framework, the dynamic field theory of movement preparation (Erlhagen & Schöner, 2002). Thus, we proposed a single mechanism for forward saccades, word skippings, refixations, and regressions, whereas in the E-Z Reader model, forward saccades and word skippings are naturally explained by the SAS mechanism. The generation of refixations is added to the model by assuming an additional refixation program to each of the model's internal state, which increases the number of states from 8 to 14 (Reichle et al., 1998).[35]

The number of model parameters is comparable between SWIFT and E-Z Reader. Whereas for E-Z Reader, dependent measures were averaged over classes of word frequency, the fitting procedure proposed here is word-based. As a consequence, the relation of number of free parameters to number of data points is much smaller for SWIFT. Therefore, besides offering a viable alternative to the highly successful E-Z Reader model, we pro-

[33] The relationship between attention and eye movements was first noted by Rayner, McConkie, and Ehrlich (1978).

[34] A quantitative approach to estimating model complexity has been developed recently based on the concept of minimum description length (Pitt, Myung, & Zhang, 2002). This approach, however, was applied to simple models rather than to more complicated computational models such as SWIFT and E-Z Reader.

[35] In E-Z Reader 7, the internal states of the model are no longer described, but we speculate that the number is much greater than 14.

posed a new approach for model fitting, which permits the analysis of computational models to much greater detail, and more reliably.

Summary

The control of eye movements during reading requires the coordination of information processing and action selection on many different cognitive levels. The SWIFT model represents a psychologically and neurophysiologically plausible computational model of how this coordination could be achieved in a unifying framework for almost all types of eye movements observed in reading experiments: forward saccades, refixations, word skippings, and regressions. The model can reproduce a number of well-established measures of eye-movement control during reading, average fixation durations and fixation probabilities, distributions of within-word landing positions, and interword regressions. Finally, the SWIFT model can explain the IOVP effect of fixation durations based on error correction of mislocated fixations.

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(*Appendixes follow*)

Appendix A

Fitting Model Parameters

For the estimation of model parameters, we used a genetic algorithm approach. This method turned out to be very efficient for the type of optimization problems we face here. The method was developed and successfully applied to SWIFT-I (Engbert et al., 2002) and to a three-state SAS model (Engbert & Kliegl, 2001). For each sentence, 200 model realizations were run with a new set of pseudorandom numbers. For all 850 words, eight statistical measures were computed from these runs.

Genetic Algorithm Procedure

For the genetic algorithm (Goldberg, 1989; Holland, 1975; Spall, 2004), we started with a population of 50 combinations (chromosomes) of parameter values, which were chosen randomly from the specified range for each parameter (Table 3). The individual ranges of parameters were chosen in advance according to mathematical or plausibility considerations. As an example, the predictability coefficient θ in Equation 1 is naturally restricted to the interval between 0 and 1. For parameters defined on an unlimited range, we chose a plausible range of values (e.g., a range from 100 ms to 300 ms for the random timer).

Using selection, mutation, and recombination (crossover) for the temporal evolution of the population of genes, we iterated the population for several 1,000 generations. A reduction of the parameter variance over the best 50 chromosomes of the population indicated convergence of the estimates of model parameters. Also, we calculated errors of the parameter estimates from these 50 chromosomes (Table 3).[A1] The number of iterations of Equation 20 necessary for this procedure of parameter fitting can be estimated as 10^3 iterations $\times$ 10^2 sentences $\times$ 10^2 runs (virtual participants) $\times$ 10^3 generations in the genetic algorithm, which gives the order of 10^{10} iterations. Numerical simulations were run on a cluster of 12 Apple G5 (dual processor) computers, which performed these computations in less than 48 hr.

The performance of the model is defined as mean squared normalized errors of fixation durations and fixation probabilities per word. Fixation durations obtained from model simulations are denoted by T^j_n, where the subscript denotes the word ($n = 1, 2, 3, \ldots, 850$) and the superscript indicates the type of measure: first fixation duration ($j = 1$), second fixation duration ($j = 2$), single fixation duration ($j = 3$), and total reading time ($j = 4$).[A2] Next, we compute the deviation from the experimentally observed value, $\bar{T}^j_k$,

$$\Delta_T = \sum_{j=1}^{4} \sum_{k=1}^{850} \left(\frac{T^j_k - \bar{T}^j_k}{\sigma(T^j_k)} \right)^2, \tag{A1}$$

where $\sigma(T^j_k)$ denotes the standard deviation of the simulated fixation durations.

The four different measures of fixation probabilities P^j_k—skipping probability ($j = 1$), probability for two fixations ($j = 2$), probability for three or more fixations ($j = 3$), and regression probability ($j = 4$)—were evaluated analogously to measures of fixation durations,

$$\Delta_P = \sum_{j=1}^{4} \sum_{k=1}^{850} \left(\frac{P^j_k - \bar{P}^j_k}{\sigma(P^j_k)} \right)^2, \tag{A2}$$

where $\sigma(P^j_k)$ represents the standard deviations of the probabilities.

In order to fit the distributions of fixation durations, we computed the deviation of the simulated distribution of fixation durations from the corresponding distributions obtained from experimental data. Distributions of average fixation durations were calculated separately for the four measures of fixation durations from 500 bins ranging from 0 to 500 ms in steps of 1 ms. The corresponding values were denoted by D^j_k, with the subscript indicating the bin ($k = 1, 2, 3, \ldots, 500$) and the superscript indicating the fixation duration measure (as for T^j_k, see above). Thus, we obtain a third measure of deviation,

$$\Delta_D = \sum_{j=1}^{4} \sum_{k=1}^{500} \left(\frac{D^j_k - \bar{D}^j_k}{D^j_k + 1} \right)^2, \tag{A3}$$

where N^j_F is the total number of fixations in each measure j.

To fit the IOVP effects for first and single fixation durations, we included an additional deviation measure. Let us denote the average first and single fixation duration on a word of length k with a fixation position on letter j as $I^1_k(j)$ and $I^2_k(j)$, respectively. To reduce noise in the empirical data, we considered only words of lengths 4 to 8, that is,

$$\Delta_{I,v} = 1000 \sum_{k=4}^{8} \sum_{j=0}^{k} \left(\frac{I^v_k(j) - \bar{I}^v_k(j)}{\bar{I}^v_k(j)} \right)^2, \tag{A4}$$

where $v = 1$ and $v = 2$ represent first and single fixation durations, respectively. Because single fixations represent the majority of all fixations, we doubled the weight for $\Delta_{I,2}$, that is,

$$\Delta_I = \Delta_{I,1} + 2\Delta_{I,2}. \tag{A5}$$

Finally, we combined the above four mean squared error measures in a single deviation measure,

$$\Delta = \Delta_T + \Delta_P + \Delta_D + \Delta_I. \tag{A6}$$

Because all realizations of the model simulations are stochastic, the deviation measures (Equation A6) fluctuate as well. Five runs of the model (using 200 virtual participants) resulted in the following numerical values: $\Delta = 6921 \pm 47$, where $\Delta_T = 4223 \pm 52$, $\Delta_P = 1744 \pm 27$, $\Delta_D = 390 \pm 13$, and $\Delta_I = 565 \pm 27$.

Parameter Sensitivity and Model Stability

Using the genetic algorithm procedure, we were able to analyze the evolution of parameters and errors over the iteration of generations (Figure A1). First, the complicated time course of the best parameter values over time indicated the presence of nonlinear correlations between model parameters. Second, the noise level seen in parameter uncertainty decreased over the evolution of the population of chromosomes. The relative strength of parameter errors varied considerably across parameters. We used the errors of parameters to simulate interindividual differences (see section on model parameters).

[A1] To further check the reliability of the optimization procedure, we carried out several runs of the genetic algorithm procedure, which reproduced the results within the error bars obtained from one simulation.

[A2] If one of the measures was not computable (e.g., for a word never fixated or never fixated more than once), we excluded the specific word from this analysis.

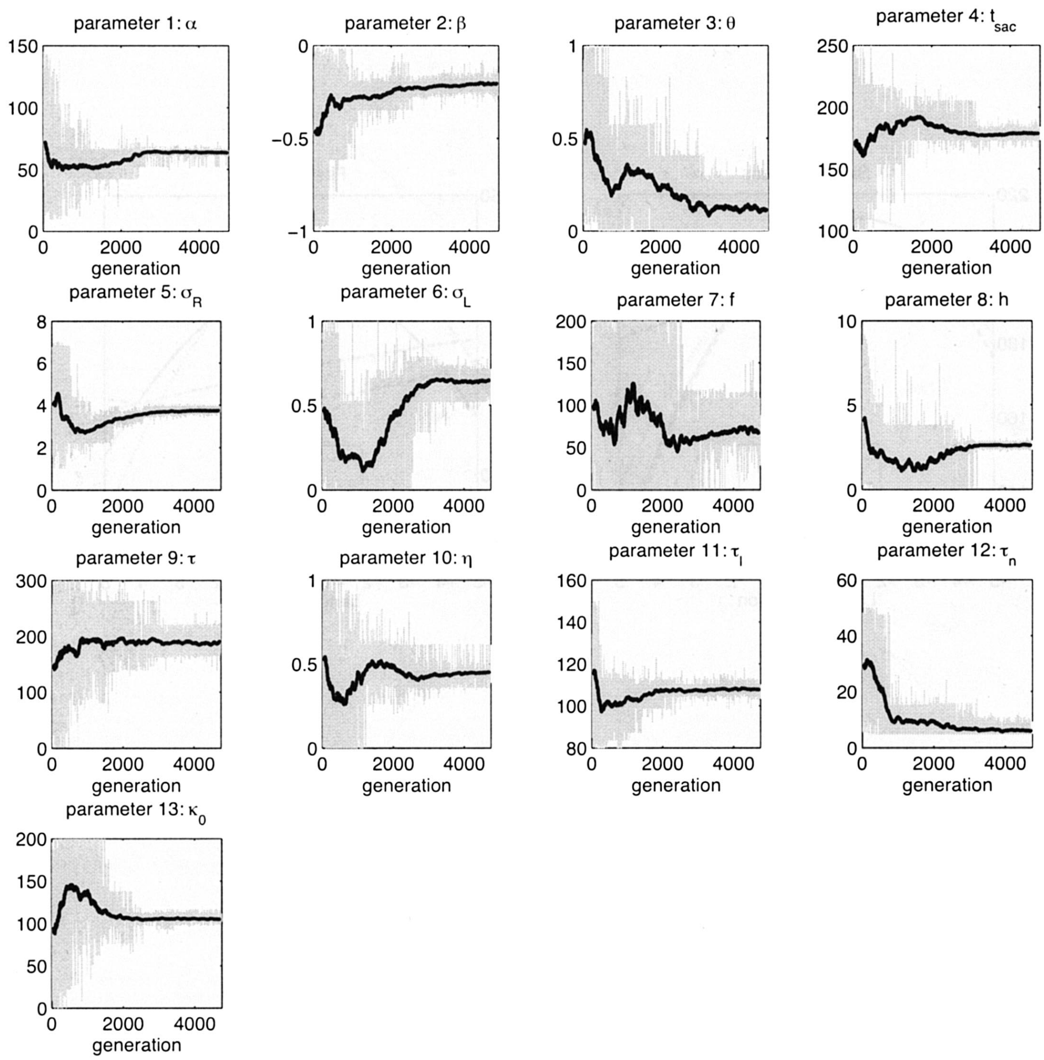

Figure A1. Evolution of parameter values in the optimization procedure by the genetic algorithm. The best value in each generation is indicated by the bold line, whereas errors are represented by the shaded area. The shrinkage of errors indicates the convergence of parameter values in the population of chromosomes.

Appendix B

Incremental Test of Model Improvement

A direct comparison of SWIFT-II with the originally proposed model SWIFT-I (Engbert et al., 2002) is not useful because of the larger number of qualitative improvements introduced in SWIFT-II. First, in SWIFT-I we wanted to test the assumption of parallel processing as an alternative to SAS models. The model did not include a physical representation of space, so that words were idealized as equally extended objects on a discrete chain. Because a more realistic attentional gradient was precluded by this approach, we used a discrete four-word processing window consisting of the fixated word, the two words to the right, and the word to the left of the fixated word, that is, an asymmetric perceptual span. As a consequence, SWIFT-I did not account for effects

Table B1
Incremental Test of Model Improvement

Error statistic		Model A	Model B	SWIFT-II
Fixation durations	Δ_T	5,218	4,457	4,130
Fixation probabilities	Δ_P	2,894	2,291	1,937
IOVP (first fixations)		−	−	+
IOVP (single fixations)		−	+	+

Note. IOVP = inverted optimal viewing position.

(*Appendixes continue*)

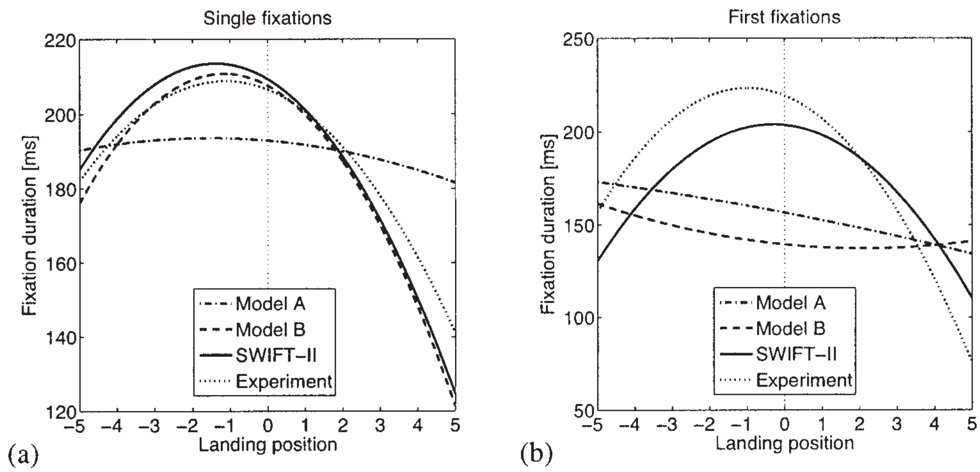

Figure B1. Average inverted optimal viewing position (IOVP) curves in different model versions. (a) Results for single fixation durations. The IOVP effect is generated by SWIFT and Model B (without latency modulation), whereas Model A (without error correction of mislocated fixations) cannot reproduce the inverted form of the curve. (b) Results for first fixation durations. The inverted form of the fixation duration as a function of within-word fixation position is reproduced by SWIFT, whereas the reduced Models A and B fail to explain the IOVP effect.

of word length, variations of within-word viewing positions, and oculomotor errors. Second, the model was implemented using an English text corpus by Schilling, Rayner, and Chumbley (1998) with a rather limited data basis (average fixation durations and fixation probabilities for classes of word frequency). Taken together, a comparison of SWIFT-II and its predecessor SWIFT-I is neither useful nor achievable in a straightforward way.

To demonstrate the power of some of our model's principles, however, we performed an incremental model comparison using two simplified versions of SWIFT-II. In Model A, we did not include Principles 6 (error correction of mislocated fixations) and 7 (saccade latency modulation), whereas in Model B we removed only the saccade latency modulation (Principle 7). Both model versions A and B were fitted to experimental data by the same techniques as SWIFT-II, described in Appendix A.[B1]

Using the optimal sets of parameters for all three models, we performed a separate run to generate data for an analysis of goodness of fit on measures for fixation durations and fixation probabilities (see Appendix A). Goodness of fit decreases (i.e., Δ_T and Δ_P increase) in the reduced Models A and B (see Table B1). Generally, we expected costs (in terms of a poorer fit) if we implemented mechanisms for the explanation of IOVP effects, which were not compatible with the implicit pattern in the experimental data. Because goodness of fit increased both with respect to fixation durations, Δ_T, and with respect to fixation probabilities, Δ_P, the additional Principles 6 and 7 are compatible with the experimental data.

Next, we investigated the performance of each of the models on the IOVP effect qualitatively. To determine the form of the curves for average fixation durations as a function of within-word fixation positions, we estimated coefficients for a second-order polynomial for a plot of IOVP effects for both first and single fixation durations (e.g., Figure 15). The resulting polynomial fits are plotted in Figure B1. Although Model A fails to reproduce any of the inverted U-shaped curves, the additional mechanism of error correction of mislocated fixations (Principle 6) in Model B can explain the inverted U shape in the IOVP effect for single fixation durations (see Figure B1a). Thus, these simulations illustrate that the additional value of the latency modulation (Principle 7) in the full model, SWIFT-II, is to reproduce the IOVP effect for first fixation durations (see Figure B1b).

In summary, our simulations of the SWIFT model suggest that the IOVP effect of single fixation durations is generated by a mechanism of error correction of mislocated fixations (Principle 6), whereas for first fixation durations it seems necessary to include a latency modulation of saccade programming (Principle 7) to reproduce the IOVP effect. These findings can also explain the discrepancies between experimental data and simulation results obtained from a "toy" model (based on Principle 6) of the IOVP effect discussed in a recent article (Nuthmann et al., 2005).

[B1] Because the IOVP effect cannot be explained by Models A and B, however, the deviation measures for the IOVP effects of first and single fixation duration were not included in the parameter estimation procedure (see Appendix A, Equation A6).

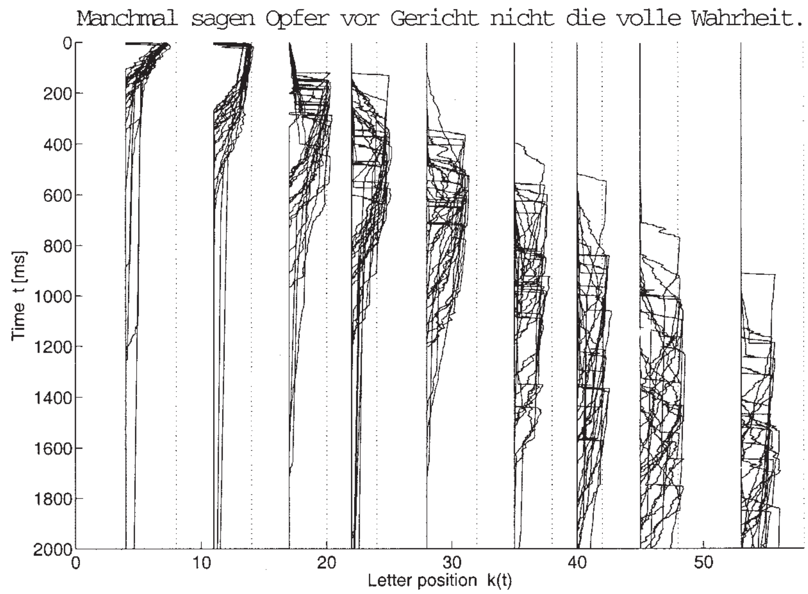

Figure C1. Temporal evolution of activations $\{a_n(t)\}$ for $N = 20$ runs of the SWIFT model using Sentence 17 of the Potsdam Sentence Corpus. The temporal evolution of the model induces a fast separation of activations between different runs.

Appendix C

Dynamical Analysis of SWIFT

The SWIFT model is a (stochastic) nonlinear dynamical system with time delay, a class of models that can generate very rich behavior (Glass & Mackey, 1988). Although the complexity of behavior generated by our model is qualitatively as rich as the experimentally observed eye movements, the mathematical analysis of model simulations provides new insight into the underlying principles of eye-movement control. Our analysis is based on concepts developed in the theory of dynamical systems (Guckenheimer & Holmes, 1983; Kaplan & Glass, 1995; Strogatz, 1994).

The SWIFT model is based on the set of N_w lexical activations $\{a_n(t)\}$, where N_w is the number of words in a given sentence. Thus, the dynamical behavior can be represented in an N_w-dimensional state space.[C1] Here, we show that the dynamical behavior can actually be approximated by a simpler system in two dimensions during each fixation. Analyses of this type may prove very useful for comparing computational models of eye-movement control in reading with respect to underlying model complexity.

The two main sources of *stochasticity* are related to saccade timing and saccade target selection, because the temporal control of fixation duration is performed by an autonomous saccade generator, which produces stochastic intervals, and the spatial control of fixation position is performed by a stochastic target selection mechanism (Equation 10) and additional oculomotor noise. During fixations, the temporal evolution of the set of activations (Equation 7), is a system of ordinary differential equations, which will generate *deterministic* behavior, although this system is perturbed by noise, because word processing is implemented as a random walk. Because SWIFT combines properties of stochastic and deterministic dynamical systems, we investigate the degree of determinism of the dynamics.

In the first step of our analysis, we compare several runs of the model in the same plot of the set of activations $\{a_n(t)\}$ over time t (see Figure C1). Although the time evolutions of activations are rather similar across runs for the first words of the sentence, the plot indicates that there is a fast divergence of the trajectories between different model runs toward the end of the sentence. Thus, we cannot directly compute the variance of trajectories from a simple plot of activations over time.

One solution to this problem is to trace the time evolution of deterministic dynamical systems in a vector space, called the *phase space.* The phase space is important for uniquely defining the dynamical state of the model, which permits (short-term) predictions of its future temporal evolution. In SWIFT, the change of activation during fixation can be visualized in a vector space with as many dimensions as there are words in a given sentence (i.e., the phase space is N_w-dimensional). During fixation of word *n,* however, the activation for most of the words is close to zero (see Figure C1). This is reflected by the observation that the most frequent saccades are (one-word) forward saccades (54%), word skippings (two-words forward, 19%), and refixations (16%). Thus, activations $a_n(t)$, $a_{n+1}(t)$, and $a_{n+2}(t)$ capture the dynamics in 89% of all saccades. Therefore, we introduce the *locally reduced* phase space for fixation on word n as the vector space $(a_n(t), a_{n+1}(t), a_{n+2}(t))$.

A further reduction of the dimension of the locally reduced phase space is obtained by the mapping from activations $\{a_n(t)\}$ to probabilities $\{\pi_n(t)\}$ (see Equation 10). The fact that saccades targeting words n, $n + 1$, and $n + 2$ represent 89% of all saccades is reflected by the observation that $\pi_n(t) + \pi_{n+1}(t) + \pi_{n+2}(t) \approx 1$ for all t. As a consequence, we can eliminate $\pi_n(t)$ as a dynamical variable (i.e., the dimension is further reduced by 1). Therefore, we use the two-dimensional locally reduced phase space $\mathcal{P} = [\pi_{n+1}(t), \pi_{n+2}(t)]$ (during fixation of word n) for the analysis of SWIFT (Figure C2a). For each run of the model we obtain a *trajectory* in phase space. Because $\pi_{n+1}(t) + \pi_{n+2}(t) \leq 1$ for all t, trajectories are bounded to the left triangle of the panels. A glance at the plot in Figure C2a shows that the trajectories are rather erratic.

[C1] For the representation of a dynamical system, we use the more rigorous concept of the *phase space* as described below.

(*Appendixes continue*)

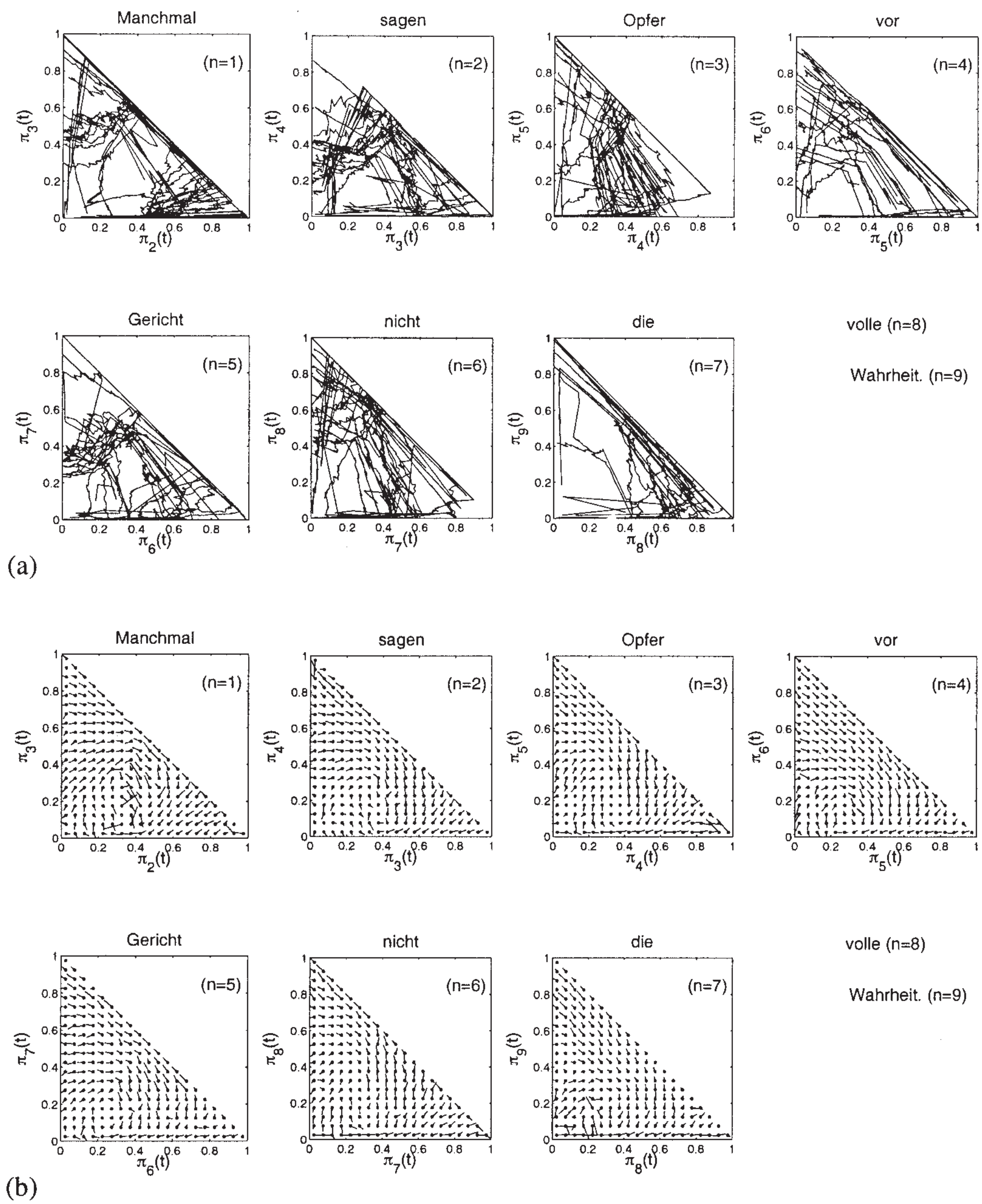

Figure C2. Visualization of SWIFT's temporal evolution in reduced phase space. (a) Plot of probabilities $\pi_{n+2}(t)$ versus $\pi_{n+1}(t)$ during fixation of word n for 20 runs of the model. (b) Phase flow estimated by average directional vectors in a coarse-grained version of the locally reduced phase space $\mathcal{P}$ from 200 runs.

To extract the *phase flow* generated by the SWIFT model, we compute average directional vectors from many runs of the model in a coarse-grained version of the locally reduced phase space $\mathcal{P}$ (Kaplan & Glass, 1992).[C2] The phase space $\mathcal{P}$ is coarse-grained into a 20 × 20 grid. Each pass k of a trajectory through box j generates a vector of unit length, called the *trajectory vector* $\vec{v}_{kj}$. After simulation of 200 trajectories, we calculate the resultant vector from the vector addition of all passes through the box

$$\vec{V}_j = \frac{1}{n_j} \sum_{k=1}^{n_j} \vec{v}_{kj}, \quad \text{(C1)}$$

where n_j is the number of passes through box j. The result is a coarse-grained estimate of the vector field of the model (see Figure C2b).

To describe the time evolution qualitatively, we use the illustration in Figure C3. Trajectories enter the plane when fixation on word n starts; that is, $a_n(t)$ dominates the set of activations. Therefore, trajectories start with small values $\pi_{n+1} > \pi_{n+2}$, because word $n + 1$ typically received more preview than word $n + 2$. Because lexical processing rate will be higher for

[C2] This method was originally proposed for the analysis of experimental data.

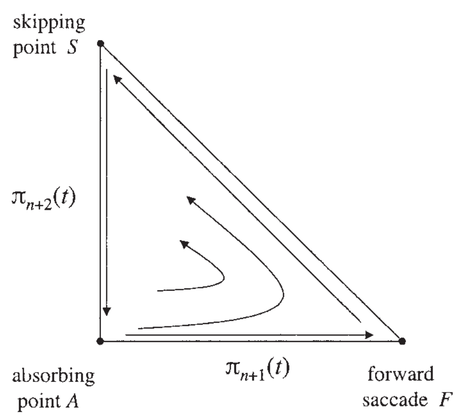

Figure C3. Schematic illustration of the phase flow in locally reduced phase space $\mathcal{P}$ during fixation of word *n*.

word $n + 1$ than for word $n + 2$, the trajectory will show a slope <1 initially. Whenever point F is reached, a forward saccade will occur with probability 1, because $\pi_{n+1} = 1$ and $\pi_{n+2} = 0$. Alternatively, the skipping point S can be reached by the trajectory, which results in a skipping, because $\pi_{n+1} = 0$ and $\pi_{n+2} = 1$. For infinitely long fixation durations on word *n,* both word $n + 1$ and word $n + 2$ will be completely processed; that is, the origin of the plane is *globally absorbing.*

The qualitative analysis demonstrates that the time evolution of the set of lexical activations shows clear properties of a deterministic dynamical system. This is a qualitative difference to SAS models, which are based on stochastic transition rules for a finite number of internal states (Engbert & Kliegl, 2001; Reichle et al., 1998). Furthermore, the dynamics are low-dimensional and can be described by the two variables π_{n+1} and π_{n+2}. The N_w-dimensional phase space collapses onto a two-dimensional subspace, where the dynamical behavior of the model unfolds. Thus, whereas the SWIFT model can potentially generate high-dimensional behavior (i.e., parallel processing of many words), the dynamical behavior is low-dimensional, with three words typically activated at a time.

Appendix D

Results on Gaze Duration

An important measure of eye-movement behavior during reading is gaze duration, which is defined as the sum of the duration of the first fixation and the durations of all direct refixations. We argued that gaze duration might be not a good measure of fixation duration for model fitting, because it represents a processing measure from a variety of different eye trajectories. For the same reason, we used an alternative definition of first fixation duration: First fixation duration is the average of the durations of all first fixations, which are followed by at least a second fixation. This definition explicitly excludes cases of single fixations.

To complement the simulation results, however, we present the results on gaze duration and on the traditional measure of first fixation duration (including single fixations) in Figure D1.

Finally, we note that there is no single measure of fixation duration that gives a comprehensive characterization of processing time. This fact is adequately reflected in Rayner's (1998, p. 377) statement that "It thus appears that any single measure of *processing time per word* is a pale reflection of the reality of cognitive processing."

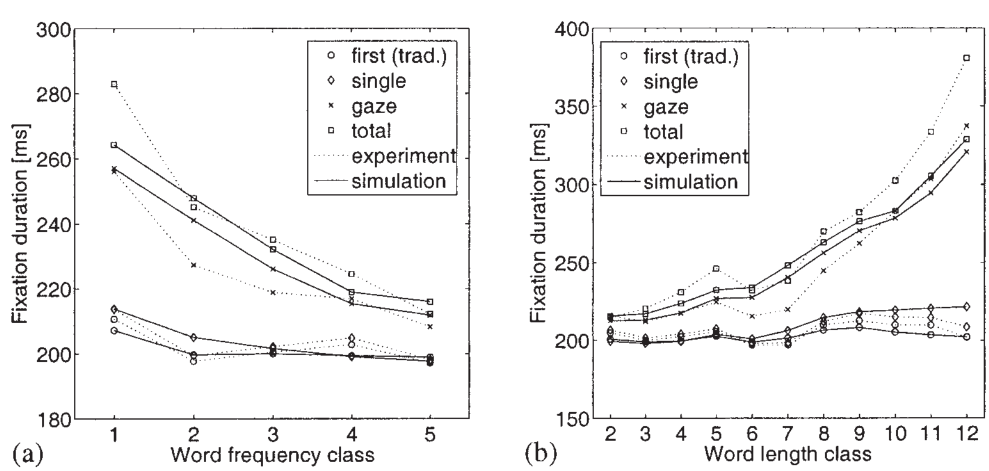

Figure D1. Results for gaze duration and traditionally defined first fixation duration. (a) Fixation duration as a function of word-frequency class. (b) Fixation duration as a function of word length.

Received November 22, 2004
Revision received April 25, 2005
Accepted May 9, 2005 ■