The Emergence of Adaptive Eye Movements in Reading

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Abstract

Simulations were completed using artificial reading "agents" that are subject to known physiological (e.g., limited visual acuity) and psychological (e.g., limited attention) constraints and capable of learning to move their eyes and allocate attention to read as efficiently as possible. These simulations indicate that agents learn when and where to move their eyes to attain maximal reading efficiency, generalize this behavior from training sentences to novel test sentences, and use word length to predict word-identification times and thereby make optimal decisions about when to initiate saccadic programming—even if word length is only moderately predictive of word-identification times. These results suggest that humans may exploit even modestly informative cues in learning to decide when to move their eyes during reading.

Keywords: Attention; Eye Movements; Genetic Algorithms; Neural Networks; Reading; Reinforcement Learning

Introduction

One of the outstanding unanswered questions in the psychology of reading (Rayner & Pollatsek, 1989) is: To what extent are the moment-to-moment decisions about *when* to move the eyes during reading determined by cognition? Attempts to answer this question can be divided into three theoretical "camps" (Reichle, 2006; Reichle, Rayner, & Pollatsek, 2003).

The first maintains that when the eyes move is largely determined by the constraints imposed by the visual and oculomotor systems (e.g., limited visual acuity). Advocates of this *oculomotor-control account* (Feng, 2006; McDonald, Carpenter, & Shillcock, 2005; Reilly & O'Regan, 1998; Suppes, 1990; Yang, 2006) argue against an eye-mind link in reading, and maintain that individual fixation durations provide only minimal information about ongoing lexical and/or linguistic processing difficulty.

According to the second "camp," most decisions about when to move the eyes are determined by the activity of an autonomous random timer that causes the eyes to move at a rate that reflects a reader's comprehension goals and overall text difficulty, with cognition only intervening to inhibit saccadic programming when processing difficulty is encountered and thereby lengthening fixation durations. Advocates of this *autonomous-timer account* (Engbert, Longtin, & Kliegl, 2002; Engbert et al., 2005; Reilly & Radach, 2006) argue for a weak eye-mind link, with individual fixations occasionally reflecting ongoing lexical or linguistic processing difficulty.

Finally, the third "camp" maintains that the eyes and mind are tightly coupled, with the completion of some cognitive process (e.g., lexical access) being the "trigger" that normally causes the eyes to move from word to word during reading. Advocates of this *cognitive-control account* (Just & Carpenter, 1980; Reichle et al., 1998; Reichle, Warren, & McConnell, 2009; Reilly, 1993; Salvucci, 2001) argue for a strong eye-mind link, with individual fixation durations usually reflecting local processing difficulty.

Perhaps not too surprisingly, all three theoretical positions have been remarkably successful explaining the basic patterns of eye movements that are observed during reading; each position has provided one or more computational models that formally instantiates the core assumption of their respective positions and that simulate many or all of the "benchmark" findings related to eye-movement behavior in reading (Reichle et al., 2003). This makes it difficult to evaluate the models purely on the basis of their ability to account for data, and because the models make different a priori assumptions about the factors that guide readers' eye movements (e.g., how attention is allocated), model evaluation is like the proverbial problem of "comparing apples and oranges." The present simulations therefore adopt an entirely different approach to understanding eye-movement control in reading.

Rather than developing a computational model around a priori assumptions about the precise manner in which perception, cognition, and motor control guide eye movements in reading, the present approach is a direct extension of the work reported by Reichle and Laurent (2006). In this work, artificial reading "agents" that were subject to known physiological (e.g., limited visual acuity) and psychological (e.g., limited capacity attention) constraints were given the task of learning how to move their eyes and attention so as to "read" (i.e., identify sequences of "words") as efficiently as possible. The key results of this work were that the agents learned: (1) to direct their eyes towards the centers of words, the viewing location that afforded the most rapid identification of the words; (2) to use word length to predict when a given word would be identified, and then initiate saccadic programming to move its eyes from that word right as it was identified; and (3) to incur local fixation duration costs by identifying short, easy-to-identify words from peripheral vision, and thereby avoiding more costly saccades to those words.

The present simulations replicate and extend the Reichle and Laurent (2006) results using artificial agents that are capable of learning to move their eyes and attention via reinforcement learning (Sutton & Barto, 1998). However, in contrast to the Reichle and Laurent agents, the present agents were implemented using *artificial neural networks* (*ANN*s), and we demonstrated in two simulations that the behavior of these agents: (1) generalizes to novel sentences and words; (2) can be learned even in less than optimal learning conditions; and (3) is generally congruent with assumptions of cognitive-control theories. The theoretical implications of these results will be discussed after the simulation results are described.

General Simulation Method

The artificial reading "agents" that were used in the present simulations were given the task of learning how to "read" (i.e., identify sequences of words in their canonical order) as efficiently as possible. These words could vary in terms of their length (1-8 letters) and/or the time required for their identification (2-14 time steps). The agents learned to perform this task (subject to various constraints, discussed below) using *trajectory sampling*, a variant of the *value iteration* reinforcement-learning algorithm (Sutton & Barto, 1998) that is often used with large-scale problems. This algorithm is specified by:

```
i = 0
for all initial S:
   Vi(S) = ANN(S)
   repeat
      i = i + 1
      if (random value < greed) then:
         Vi(S) = Vi-1(S) + ε{max_action∈M[reward(S, action)
                + γ Vi-1(S′)] – Vi-1(S)}
      else random action
until learning has completed.
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where i indexes the learning iteration, $V_i(S)$ is the value associated with state S at time i, and M is the set of permissible actions from a given state. There are three parameters: ε (= 0.5) controls the learning rate, *greed* (= 0.5) controls how often an agent exploits what it already knows in selecting actions versus exploring the consequences of randomly selected actions, and γ (= 0.9) determines how much the agent weighs the reward that is anticipated from the next state, S', versus the immediate reward that it receives from the action that it selects. Each state, S, consists of information that is available to the agent at any given point in time (see Table 1). The agents can perform one of three actions: (1) continue attending (i.e., lexically processing) the current word; (2) shift attention to the next word; and (3) request an eye movement of ±10 character spaces. An agent selects the actions that result in the most (anticipated) reward, being "rewarded" +1 for every identified word and "punished" -1 for every time step spent processing a sentence. Learning continues until the values of the states reach asymptote.

Table 1. State information (S) used by agents.

#	Available Information
1	Attended word (i.e., word$_n$) identified? (Y/N)
2	# time steps processing word$_n$
3	# spaces between center of word$_n$ and fixation
4	Length of word$_n$
5	Length of word$_{n+1}$
6	Length of word$_{n-1}$
7	Saccade being programmed? (Y/N)
8	Length (# spaces) of intended saccade
9	# time steps programming saccade

As mentioned, the agents are subject to several constraints. First, visual acuity is limited, so that the rate of lexical processing decreases as the spatial distance between the agent's center of vision and the center of the word being processed increases (i.e., a word that takes N time steps to identify when its middle letter is fixated will take 1 additional time step to identify for each character space of disparity between the letter being fixated and the center of the word). Saccades also require 3 time steps to program and 1 time step to execute, and are subject to Gaussian (μ = 0; σ = 1) random error. Finally, because the perceptual span is known to be of limited spatial extent (Rayner & Pollatsek, 1989; Rayner, 1998), the agents were only allowed to process one word at a time, instantiating the assumption that attention is allocated serially during reading (e.g., Reichle et al., 1998) or approximating the assumption that attention is allocated as a gradient—albeit a tightly focused one (e.g., Engbert et al., 2005). Although this assumption about attention is quite controversial (e.g., see Reichle et al., 2009), it was intended as a simplifying assumption to make the simulations as tractable as possible.

In the Reichle and Lauent (2006) simulations, the value of each state, $V_i(S)$, was stored in a look-up table (i.e., one value per combination of dimensions in Table 1). In the present simulations, the values were learned and stored in the connection weights of an ANN whose architecture and principle weights were selected using *NeuroEvolution of Augmenting Topologies* (*NEAT*) (Stanley & Miikkulainene, 2002) and whose weights were optimized via the *Covariance Matrix Adaptation Evolution Strategy* (*CMA-ES*; Hansen, Müller, & Koumoustsakos, 2003) when trapped in local maxima. Figure 1 is a schematic diagram of how the NeuroEvolution and CMA-ES algorithms are used in conjunction with task-specific training to select network architectures that are well suited to solve the types of problems explored in this article.

Each network was comprised of nine input units (one per dimension in Table 1), one bias unit, one output unit (representing the learned value of each state), and an unspecified number of hidden units. In contrast to many neural networks, the hidden units were not strictly layered, but could be configured in a variety of ways (e.g., as additional bias units; see Fig. 1). The activation of input unit *i* when given some value *x* of one of the dimensions in Table 1 was scaled to the interval [-1, 1] using:

$$act_i(x) = \{x - [\max(x) / 2]\} / [\max(x) / 2]$$

where the function "max" returns the maximum value of the dimension. (Note that $act_i(x) = -1/1$ when Dimensions 1 and 7 equal false/true.)

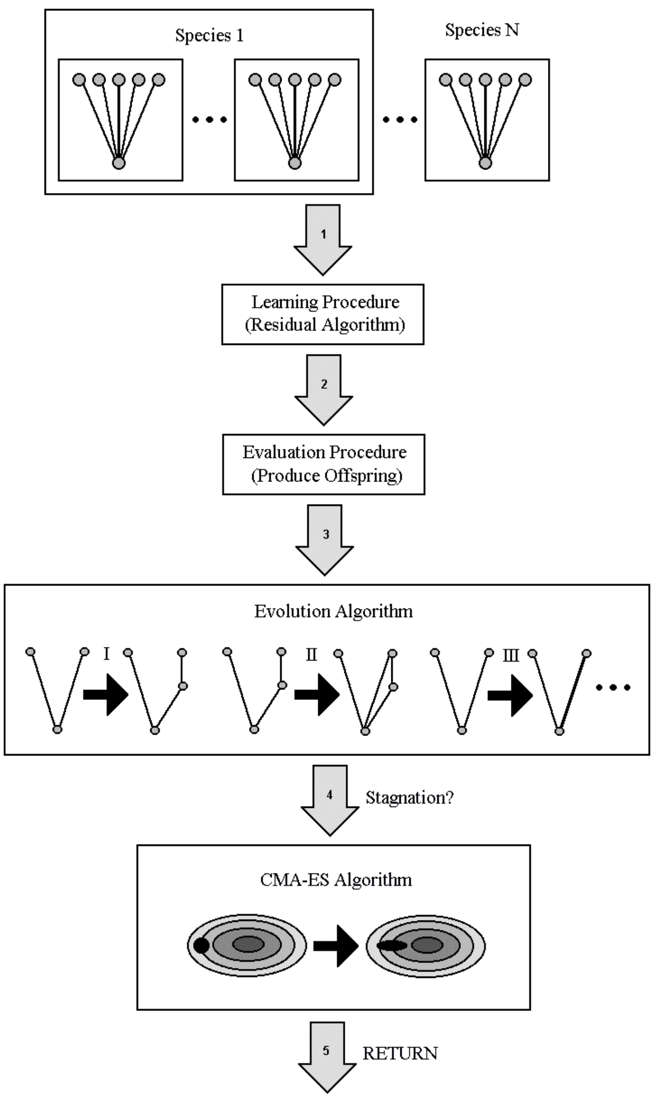

Figure 1. Method use to evolve and train agents.

This NeuroEvolution algorithm was used to select network architectures that were adapted to use the value iteration reinforcement-learning algorithm (via using a residual algorithm to implement back-propagation in the ANNs) for the tasks that are the focus of this article—learning to move the eyes and attention to read efficiently. The CMA-ES algorithm was used to optimize weights when optimization stagnated. Each reported simulation is based on populations of 100 individuals evaluated across 300 generations to solve the tasks of interest. Each individual networks agent also learned to perform its task using value iteration across five learning trials and using the specific training regimens.

Simulation 1

The first simulation replicated and extended the Reichle and Laurent (2006) results using agents implemented as ANNs (as described above) and various novel test sentences.

Method. Five agents were trained on a corpus of five 8-word "sentences" comprised of random permutations of 1-, 3-, 5-, and 7-letter "words." (These sentences were randomly selected from 20 used by Reichle & Laurent, 2006.) The first and last words were always 1-letter in length and required 2 time steps to identify, and always excluded from our analyses because their processing started/ended abruptly. The remaining 1-, 3-, 5-, and 7-letter words respectively required 2, 6, 10, and 14 time steps to identify when fixated from their central letters. After training, agents were tested on: (1) the same five sentences; (2) five novel 8-word sentences comprised of different random permutations of 1-, 3-, 5-, and 7-letter words; and (3) five 8-word sentences comprised of random permutations of 2-, 4-, 6-, and 8-letter novel words.

Results. Figure 2 shows the simulated fixation landing-site distributions on the words, as a function of their length and whether the sentences being using used to evaluate the agents were old (i.e., used during training), novel, or comprised of novel words (i.e., 2-, 4-, 6-, and 8-letter words). (In all of the figures shown below, the data points indicate the condition means and the error bars indicate the standard errors of the means.) As indicated, the agents learned to direct their eyes towards the centers of the words because this was the viewing position that afforded the most rapid identification of the words. However, because of saccadic error, the fixation landing sites are approximately normally distributed, in line with what is observed with human readers (McConkie et al., 1988, 1991; Rayner, Sereno, & Raney, 1996). Finally, the behavior generalized across both novel sentences and words.

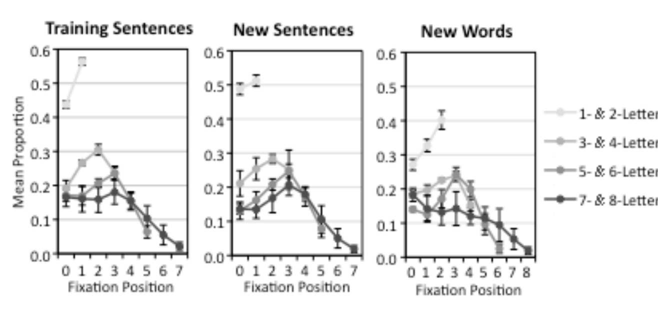

Figure 2. Simulated fixation landing-site distributions.

Figure 3 shows the mean probabilities of making a single fixation, making two or more fixations, or skipping, again as a function of word length and the nature of the test sentences. As the figure shows, agents tended to either make a single fixation on or skip the shorter words, and to make two or more fixations on the longer words. These results are consistent with what is observed with humans (Rayner et al., 1996) and did not vary by testing condition.

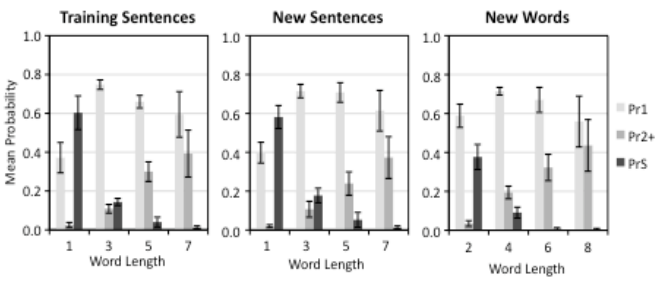

Figure 3. Simulated fixation probabilities.

Figure 4 shows the mean simulated values of five dependent measures (in time steps), again as a function of word length: (1) *first-fixation duration* (*FFD*), or the duration of the first fixation on a word during the first pass through the sentence; (2) *gaze duration* (*GD*), or the sum of all first-pass fixations; (3) *total-viewing time* (*TT*), or the sum of all fixations, irrespective of whether they occur during the first pass; (4) *word-identification times* (*ID*), or the time spent processing the words; and (5) *saccadic-programming initiation times* (*SPIT*), or the time spent processing word$_n$ prior to initiating the saccade that moved the eyes to word$_{n+1}$. As Figure 4 indicates, the measures increased with increasing word length (which is perfectly correlated with identification time), but with the mean processing time being longer than the minimal identification time because saccadic error often caused words to be processed from poor viewing locations, where lexical processing was slower. Importantly, if an agent spent N time steps processing word$_n$, then it on average spent approximately N-3 time steps processing word$_n$ before initiating saccadic programming to move its eyes to word$_{n+1}$. This is an optimal strategy for deciding when to move the eyes because initiating saccadic programming any earlier would cause the eyes to leave word$_n$ prematurely, resulting in it being processed more slowly from word$_{n+1}$ (because of reduced visual acuity). Conversely, initiating saccadic programming any later would cause the fixations to be unnecessary long in duration. Thus, by initiating saccadic programming at the observed times, an agent insures that, in most cases, the eyes move from word$_n$ right when it has been identified. (It is also worth noting that this strategy is similar to the “familiarity check” assumption of the E-Z Reader model of eye-movement control during reading, where a preliminary stage of lexical processing is the “trigger” that initiates saccadic programming; Reichle et al., 1998, 2003, 2009.)

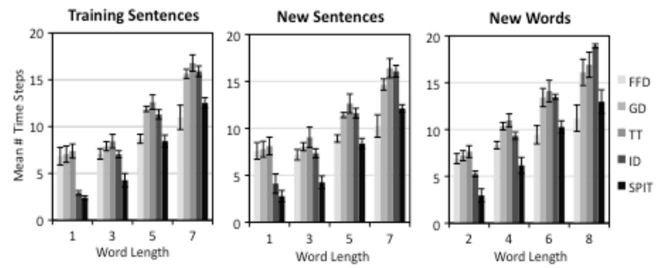

Figure 4. Simulated time-based dependent measures.

These results of Simulation 1 replicate and extend the key findings reported by Reichle and Laurent (2006) by showing that the reading agents, implemented as ANNs, are able to generalize from a small set of training sentences to sentences containing novel configurations of words. This is methodologically important because it shows how ANNs might be used to solve large-scale reinforcement learning problems that might otherwise be impossible to solve (e.g., a look-up table version of the agents would require the storage and updating of the more than 6 million different states listed in Table 1). This demonstration also makes it possible to explore more complex contingencies between eye-movement behavior and lexical variables, as described next.

Simulation 2

The second simulation examined the consequences of training on a more realistic sentence corpus—one in which word length is only moderately predictive of the time required to identify words.

Method. Five agents were trained and tested on five 8-word sentences in which 1-, 3-, 5-, and 7-letter words required 4-9 time steps to identify, and where word length was only moderately correlated to word-identification times across the corpus (r = 0.31).

Results. The simulated landing-site distributions, fixation probabilities, and time-based measures (grouped by both word length and identification time) are shown in Figures 5-7, respectively. As indicated in the left panel of Figure 5, the agents learned to direct their eyes towards the centers of words because this location afforded the most rapid identification of words. And as the left panel of Figure 6 shows, the agents were also more likely to make single fixations on or skip the shorter words, and make two or more fixations on the longer words. Both of these findings are consistent with human readers (McConkie et al., 1988, 1991; Rayner, 1996) and the results of Simulation 1. The right panels of Figures 5 and 6 indicate that similar word-targeting behaviors were evident when the words are grouped by their identification times, but that there are some irregularities (e.g., bimodal landing-site distributions with the more-difficult-to-identify words) because these items included a mixture of both short and long words.

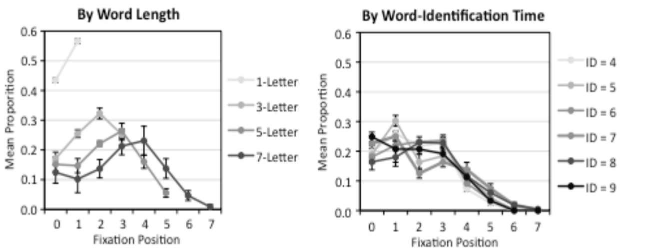

Figure 5. Simulated fixation landing-site distributions, by word length (left) and identification times (right).

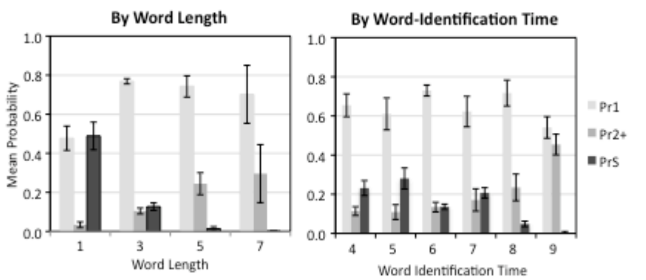

Figure 6. Simulated fixation probabilities, by word length (left) and identification times (right).

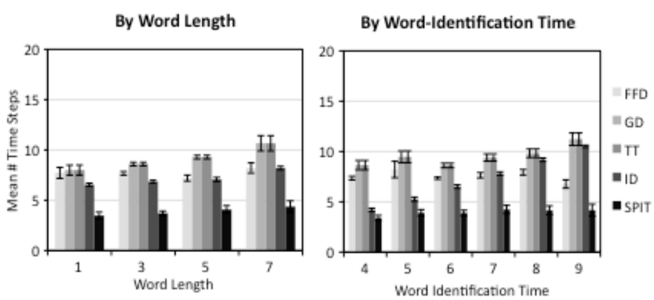

Figure 7. Simulated time-based measures, by word length (left) and identification times (right).

Finally, the most striking result from Simulation 2 is that the agents learn to use word length information to predict the time required to identify words, and then used this knowledge to program saccades so that the eyes would leave a word right as it was identified. This "strategy" is similar to the one that was adopted by the agents in Simulation 1, even though the relation between word length and identification times was much weaker in Simulation 2 (r = 0.31) than Simulation 1 (r = 1). And as the left and right panels of Figure 7 indicate, this strategy was evident irrespective of whether the words are grouped by their length or by their identification times.

General Discussion

The simulations reported in this article replicated the Reichle and Laurent (2006) results by showing that "intelligent" eye-movement behavior can emerge from artificial reading agents that are subject to fairly uncontroversial physiological and psychological constraints and that are capable of learning to coordinate attention and eye movements to support efficient reading. Simulation 1 extended the Reichle and Laurent results by implementing the reading agents within an ANN and then showing that the agents' eye-movement behaviors generalize to novel sentences and words. And importantly, the agents used word-length cues to predict when words would be identified, and then used this knowledge to learn when to initiate saccadic programming. Simulation 2 indicated that the agents learned the same eye-movement behaviors, including learning to use word length to initiate saccadic programming in an optimal manner—even though word length was only moderately predictive of word-identification time.

The simulation results have important theoretical implications for our general understanding of eye-movement control in reading and the specific questions of what determines when our eyes move during reading. First, the simulations suggest how information that is predictive of when a word will be identified can be used to initiate saccadic programming in a manner that affords efficient reading. In the absence of such predictive information, it may be optimal to either simply wait until word$_n$ has been identified before initiating saccadic programming to move the eyes to word$_{n+1}$, or to base the decision on the mean time required to identify word$_n$. Although both of these strategies prevent the eyes from moving prematurely (which would then slow reading considerably because words would have to be identified from poorer viewing locations), the strategies are also conservative because they often produce unnecessarily long fixations. This suggests that any strategy that simply ignores lexical processing difficulty and uses saccadic programming and visual acuity constraints to decide when to move the eyes will not be optimal because it ignores information (about the rate of lexical processing) that can be used to inform those decisions. This conclusion provides one argument against oculomotor-control theories of eye-movement control in reading (Feng, 2006; McDonald et al., 2005; Reilly & O'Regan, 1998; Suppes, 1990; Yang, 2006). And although our results admittedly say less about the feasibility of autonomous-timer theories (Engbert et al., 2002, 2005), such theories are not parsimonious if decisions about when to move the eyes can be made using information that is readily available to the reader (i.e., information about lexical processing difficulty). In other words, it is not parsimonious to posit an autonomous timer that is occasionally overridden by lexical processing difficulty if this information is itself sufficient to decide when to move the eyes in an optimal manner.

Second, the simulations suggest that humans may exploit cues that may be only modestly predictive of lexical processing difficulty in learning to decide when to initiate saccadic programming. These cues probably include word length, but also orthographic cues (e.g., prefixes and suffixes, unusual letter sequences, etc.), and possibly cues that are generated via top-down processing (e.g., the syntactic and/or semantic constraints imposed by a word's prior sentence context). It is an open question as to how these different sources of information are combined in making moment-to-moment decisions about when to move the eyes during reading, but a vast experimental literature (e.g., for a review, see Rayner, 1998) indicates that these variables (and many others) do influence such decisions. Future simulations using our artificial reading agents will provide testable hypotheses regarding this question.

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