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Simulating Letter and Word Recognition: A fuzzy logical model of integrating visual information and orthographic structure in reading*

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Abstract. A model of reading is implemented as a computer simulation to describe the perceptual recognition of letter strings and words. Visual information about letters and knowledge about orthographic structure (spelling constraints) provide independent sources of information. These sources of information are continuous and are treated as fuzzy values in fuzzy set theory. The sources are evaluated and multiplied together so that the contribution of each source is directly related to its degree of information certainty. The model is capable of describing the reader's utilization of both visual information and orthographic structure in the perceptual recognition of letters and words.

It is widely acknowledged that the reader contributes as much or more to reading than does the "information" on the printed page (Gibson & Levin, 1975; Smith, 1971). One compelling issue in reading research is how the reader's higher-order knowledge of the language interacts with lower-level perceptual analyses during reading. The specific question addressed in the present paper is how the reader combines knowledge about orthographic structure with the information derived from the visual feature analysis in letter and word recognition. Orthographic structure refers to the spelling constraints in a written language. Given the considerable amount of predictability in English writing, we ask how the reader utilizes this orthographic structure in word recognition. Visual feature analysis refers to the evaluation and utilization of component properties of letters leading to letter and word recognition. The goal of the present paper is to articulate a computer simulation model of the reader's evaluation, utilization, and integration of these two sources of information in reading.

Evaluation of the contributions of visual features and orthographic structure to word recognition can be facilitated by a detailed description of the processes involved in reading. The description is part of a more extensive model of language processing (Massaro, 1975, 1978, 1979; Massaro, Taylor, Venezky, Jastrzembski & Lucas, 1980; Massaro, Venezky, & Taylor, 1979). According to the model, reading can be viewed as a sequence of processing stages. Figure 1 presents a schematic representation of the stages of processing. At each stage of processing, memory and process

Figure 1. A stage model of reading printed text.

components are represented. Each memory component (indicated by a rectangle) corresponds to the information available at a particular stage of processing. Each process component (indicated by a circle) corresponds to the operations applied to the information held by the memory component. The memory components are temporary storages except for long-term memory which is relatively permanent. It is assumed that knowledge in long-term memory supplements the information at some of the processing stages.

During reading, the light pattern reflected from a display of letters is transduced by the visual receptors as the feature detection process detects and transmits visual features to preperceptual visual storage (see Figure 1). As visual features enter in preperceptual visual storage, the primary recognition process attempts to transform these isolated features into a sequence of letters and spaces in synthesized visual memory. To do this, the primary recognition process utilizes information held in long-term memory. For the accomplished reader this includes a list of features for each letter of the alphabet along with information about the orthographic structure of the language. Accordingly, the primary recognition process uses both the visual features in preperceptual storage and knowledge of orthographic structure in long-term memory during the primary recognition of letter strings.

The primary recognition process operates on a number of letters simultaneously (in parallel). The visual features detected at each spatial location of the letter string define a set of possible letters for that position. The primary recognition process chooses from this set of candidates the letter alternative which has the best correspondence in terms of visual features. However, the selection of a letter can be facilitated by the reader's knowledge of orthographic structure. The primary recognition process, therefore, attempts to utilize both the featural information in preperceptual storage and knowledge about the structure of letter strings in long-term memory. We assume that orthographic structure is utilized in the following manner: upon presentation of a letter string, the primary recognition process begins integrating and synthesizing featural information passed on by feature detection to preperceptual visual storage. Featural information is resolved at different rates and there is some evidence that gross features are available before the more detailed features (Massaro & Schuller, 1975). The primary recognition process is faced with a succession of partial information states. These partial information states are supplemented with knowledge about orthographic structure. Assume, for example, an initial "th" has been perceived in a letter string, and the features available for the next letter eliminate all alternatives except "c" and "e". The primary recognition process would synthesize "e" without waiting for further visual information, since initial "thc" is not acceptable, which "the" is.

The primary recognition process transmits a sequence of recognized letters to synthesized visual memory. It is assumed that the secondary recognition process transforms this synthesized visual percept into a meaningful form in generated abstract memory (see Figure 1). The secondary recognition process attempts to interpret the letter string as a word by finding the best match between the letter string

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and a word stored in a lexicon in long-term memory. Each word in the lexicon contains both perceptual and conceptual codes. The word which is recognized is the one whose perceptual code gives the best match and whose conceptual code is most appropriate in that particular context. Knowledge of orthographic structure can also contribute to secondary recognition; word recognition can occur without complete recognition of all of the component letters. Given the letters "bea" and the viable alternatives "l" and "t" in final position, only "t" makes a word, and therefore word identification (lexical access) can be achieved (Massaro, 1977).

Empirical Findings

To assess how readers utilize knowledge about the structure of written language, it is necessary to state various descriptions of this structure and then to determine how well these descriptions capture reading performance. Venezky and Massaro (1979) and Massaro et al. (1979, 1980) have distinguished between two broad categories of orthographic structure: frequency and regularity. The first category includes all descriptions derived solely from the frequency of letters and letter sequences in written texts. The second category includes all descriptions derived from the phonological constraints in English and scribal conventions for the sequences of letters in words. Although these two categories are not completely independent, the goal was to decide which general category seemed to best reflect the manner in which readers store knowledge of orthographic structure and second, to determine precisely which specific description within that category has the most psychological reality.

Massaro et al. (1979, 1980) contrasted specific frequency descriptions with a specific regularity description by comparing letter strings that varied orthogonally with respect to these descriptions. The frequency measures were either position-sensitive summed token single-letter frequency, bigram frequency, or log bigram frequency. The regularity measures were sets of rules defining legal letter occurrences (see Massaro et al., 1980, for further details about these measures of orthographic structure).

In one experiment subjects were asked to recognize lower case letters presented on a video computer terminal. On each trial, a six-letter test string was presented for a short duration followed immediately by a mask stimulus made up of random visual features. A target letter followed the test string and the subject's task was to indicate whether or not the target letter was contained in the test string. Figure 2 illustrates the sequence of events on each trial of the experiment. On a random half of the trials, the target letter was present in the

Figure 2. Schematic representation of a trial in the experiment.

preceding test string. This kind of trial is called a target trial. On the other half of the trials, the target letter was not contained in the previous test string. This kind of trial is referred to as a catch trial. Therefore, a subject's average performance will fall between 50 percent (guessing) and 100 percent correct (perfect) in the task. The exposure duration of the test string was adjusted for each subject to obtain an average of 75 percent correct across all conditions in the task. Figure 3 gives examples of the five types of letter strings used in the experiments. The test strings consisted of 40 words and four anagrams of each word, giving a total of 200 test strings. The anagram strings were either high or low in terms of summed single-letter positional frequency and were either regular or irregular in terms of orthographic structure. Single-letter positional frequency is the frequency with which a letter occurs in a specific position

Words	winter change turned (1293)	Positional Frequency	
		High	Low
Orthographic Regularity: Regular		brawn chager dlunet (1438)	brwin yreach tirdun (540)
Orthographic Regularity: Irregular		wrnbei ahcger nlnuet (1421)	nlewi hreagc edtrnu (526)

Figure 3. The five types of items and examples of each type used in the experiment. The number in each cell is the average summed single-letter positional frequency for that item type.

of words six letters in length. The summed single-letter positional frequency of a string is just the sum of the letter frequencies across the six positions. Regular strings did not violate any of the rules defining legal occurrences of letters. Irregular strings violated at least one of these rules.

The results of this experiment are shown in Figure 4. As can be seen in the figure, the type

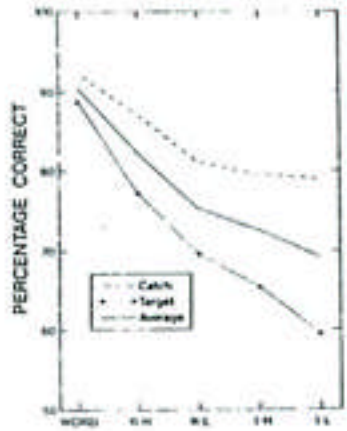

Figure 4. Percentage correct as a function of display type for target and catch trials. (R-H is regular-high, R-L is regular-low, I-H is irregular-high, and I-L is irregular-low anagrams).

of letter string had a significant effect on performance on both catch and target trials. There were significant advantages in performance for words over the anagram strings, for regular anagrams over irregular anagrams, and for anagrams high in positional frequency over anagrams low in positional frequency.

The results revealed large effects of the variables of interest. A more detailed index of performance accuracy as a function of these variables is the performance on each test string. There were 200 test strings and the dependent measure used in the present analysis is the average accuracy for each of the 200 test items (taken from Massaro et al.,

Given the test item "result," the frequency goodness values for r and t in first position are computed from the goodness values for the bigrams re, ro, rc, and rg and te, to, tc, and tg. These values are

re=.0082	te=.0055
ro=.0057	to=.0065
rc=0	tc=0
rg=0	tg=0

The bigram information and the visual information derived from Visual Featural Evaluation are combined to obtain a goodness value for each bigram according to the formula

$$G(xy) = VG(x) \times VG(y) \times FG(xy) \qquad (3)$$

where G(xy) is the goodness value of bigram xy, VG(x) is the visual goodness of X, VG(y) is the visual goodness value of y, and FG(xy) is the frequency goodness of the bigram xy.

The relative goodness RG(xy), of each bigram was computed by dividing its goodness value by the sum of the goodness values of all the possible bigrams at that position.

Given these values for all possible candidate strings, a relative goodness value is computed for each candidate letter at each of the six positions in the test string. For positions one and six, a sum of the relative goodness values for all bigrams containing the candidate letter at that position is taken. For positions two through five, the sums are computed from the values given by the two bigrams sharing that position.

The goodness value for r in initial position is equal to the sum of the four bigram goodness values containing r. The goodness value for t is computed analogously. The relative goodness is then computed by forcing the r and t goodness values to sum to one by the formula

$$RG(r) = \frac{G(r)}{G(r) + G(t)} \qquad (4)$$

where RG(r) is the relative goodness of r, G(r) is the goodness of r, and G(t) is the goodness value of t.

For the letters in positions two through five in the candidate set, the goodness values are computed from adjacent bigrams. Consider the goodness of the letters in fifth position in the current example. The goodness value for l, G(l) would be equal to

$$G(l) = G(ul) = \{G(lt) + G(lf) + G(lr) + G(lk)\} \qquad (5)$$

The value G(ul) is the goodness of the bigram ul in positions 4-5 of six-letter words whereas the bigram lt is the goodness of the bigram lt in positions 5-6. The multiplicative combination of information from adjacent bigrams is another instance of the general algorithm of combining different sources of information.

The relative goodness of l, RG(l), is given by

$$RG(l) = \frac{G(l)}{G(l) + G(i) + G(k)} \qquad (6)$$

where G(i) and G(k) are determined analogously to the computation of G(l).

Note that RG(u) in fourth position would be one since it is the only letter in the candidate set.

In summary, a relative goodness value is computed for each candidate letter at each position.

Integration--Regularity Model

For each candidate string, its letters are classified as legal, semilegal, or illegal and a corresponding value of .9, .5, or .1 is assigned. A mean legality value is assigned to each candidate letter at each position by averaging the legality values for that letter at that position across the set of all candidate strings.

Consider the legality goodness, LG, values for the letters in the first position of the test item "result." The initial sequences rc and rg are legal, whereas the initial sequences re and ro are illegal. The same is true for te, to, and tc, tg. Therefore, substituting the goodness values of .9 for legal and .1 for illegal, the goodness of r, G(r) would be

$$LG(r) = \frac{.9 + .9 + .1 + .1}{4} = .5 \qquad (7)$$

The goodness of t, LG(t), would also be .5.

The visual goodness of each letter is multiplied by the legality goodness to give an overall goodness of that letter. For the letter r

$$G(r) = VG(r) \times LG(r) = .88 \times .5 = .44 \qquad (8)$$

For the letter t

$$G(t) = VG(t) \times LG(t) = .12 \times .5 = .06 \qquad (9)$$

The relative goodness of the letter r in initial position is given by

$$RG(r) = \frac{G(r)}{G(r) + G(t)} = \frac{.44}{.44 + .06} = .88 \qquad (10)$$

As can be seen, the goodness of r is completely determined by the visual goodness since r and t have equivalent legality goodness values.

The pattern classification operation and the secondary recognition operation are straightforward and are described in the main body of the text.

sensory and knowledge contributions to recognition. Second, the sources of information are assumed to be continuous and are treated as fuzzy variables within the context of fuzzy set theory (Zadeh 1965). A third property of the simulation model is the multiplicative combination of the independent sources of information. This combination rule has the consequence that the least ambiguous source of information contributes the most to interpretation of the message. Accordingly, there is no conflict between bottom-up sensory processes and top-down knowledge processes. Both contribute to recognition as a direct function of their information value. Further tests of the model will include the contribution of other sources of information such as sentential constraints in reading.

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Appendix

Explanation of the exact procedure for calculating and combining visual and orthographic structure information in the simulation of the recognition of the test items.

Visual Feature Evaluation

The visual goodness values greater than .05 for each test letter define a set of candidate letters for each position in the test string. All possible combinations of these letters determines a candidate set of test strings. Given the test word "result," the candidate set of letters and their visual goodness values at each of the six position are

Position

1	2	3	4	5	6
r(.59)	e(.37)	s(.32)	u(.55)	l(.53)	t(.38)
i(.08)	o(.08)	e(.07)		i(.10)	i(.12)
	c(.06)	c(.07)		k(.05)	r(.12)
	g(.05)	g(.07)			i(.09)
		a(.05)			

The candidate set of strings is determined by the combination of the candidate set of letters. Therefore, there are 2 x 4 x 5 x 1 x 3 x 4 = 480 strings in the candidate set for the test word "result." The same number of strings would be in the candidate set for any anagram of "result," such as the irregular-low test item "elsrtu," since these two test items have the same set of candidate letters. The letters are in different positions and, therefore, the candidate set of strings will differ for the two test items. The candidate set of letters and test strings are made available to the Frequency and Regularity Integration operations.

The visual goodness (VG) of each candidate letter at each position is transformed into a relative visual goodness (RVG) value. Considering the letters at the first position in the test item "result"

$$RVG(r) = \frac{VG(r)}{VG(r) + VG(i)} = \frac{.59}{.59 + .08} = .88 \qquad (1)$$

where RVG(r) is the relative visual goodness of r and VG(r) is the visual goodness of r. For the letter t in first position

$$RVG(t) = \frac{.08}{.59 + .08} = .12 \qquad (2)$$

Integration--Frequency Model

For each possible position-sensitive bigram in the candidate set of strings, the position sensitive log bigram frequency is assigned. The assignment is in terms of a normalized value between zero and one representing the relative frequency (proportion) of occurrences of the particular bigram in that position in six-letter strings.

Given the visual information and the regularity information for each perceivable letter at each of the six positions in the test string, the two are multiplied to obtain an overall goodness value. Overall goodness values are computed for each perceivable letter at each position in the test string. A relative goodness value for each letter was computed by normalizing the overall goodness values. This normalization forces the goodness values for all perceivable letters for a given letter position to sum to one.

Integration Models--Summary

The frequency model and the regularity model utilize identical processes for the evaluation of visual information, the combination of visual and structural information, and for the pattern classification operation. The only difference between the models is in terms of frequency versus regularity descriptions of structural information. This sole difference permits a direct comparison between the two models in terms of how well they describe the perceptual recognition of letter strings.

Pattern Classification

At this point, every confusable letter has a relative goodness value for each of the six positions in the letter string. The pattern classification operation computes a letter for each position by simply seeing a particular letter at a particular position with the probability corresponding to that letter's relative goodness value. Therefore, the outcome of the pattern classification operation was the perception of six unique letters in the string. Although a given letter was seen clearly at each position, its selection was probabilistic. The probability of seeing a letter was equal to its final relative goodness value. In the actual tests of the model, the proportion of classifications of a test letter as a particular confusable alternative was assumed to be equal to the alternative's relative goodness value. As an example, if the relative goodness value for "i," "l," and "t" in initial position were .7, .2, and .1, respectively, then the first letter was seen as "i" 70 percent of the time, as "l" 20 percent of the time, and as "t" 10 percent of the time. Therefore, if "l" was the actual test letter, then the percentage of correct identifications of the test letter would have been 20 percent.

Secondary Recognition

In one version of each model, a secondary recognition operation was included to account for the contribution of lexical status in the recognition of the letter strings. Given information about only some of the letters of a letter string, it was possible to achieve lexical access. For each word string, if the percentage of letters recognized correctly exceeded some criterion precentage correct, it was assumed that lexical access was achieved. The criterion was chosen to give predicted overall performance on the word strings roughly equal to that observed in the experiments. Given lexical access, the secondary recognition process would upgrade the number of letters seen correctly to six. As an example, with a criterion of four letters correct, if primary recognition produced the string, "winten" or "wirter," the word "winter" would be accessed and all six letters would be seen correctly.

Tests of the Models

The models were tested on the 200 six-letter test strings used by Massaro et al. (1980). The models were evaluated by correlating predicted performance with observed performance on each of the 200 test strings. Correlating predicted and observed performance on specific test items would seem to offer the most sensitive test of the models. The reader is referred to Massaro et al. (1980) for a description of the selection of the items, the experimental procedure, and the data analysis.

The correlations between the predictions of the three models and the observed results are given in Table 1.

Table 1

Correlations between predictions of the models and the observed results for 200 test strings.

Model	Correlation
Visual	.097
Visual + Lexical	.430
Visual + Frequency	.661
Visual + Frequency + Lexical	.692
Visual + Regularity	.416
Visual + Regularity + Lexical	.552

As can be seen in the table, visual information alone does not give an adequate description of the recognition of the 200 test letter-strings. Adding lexical information to the visual information via the secondary recognition process improves the description of performance.

The results of central interest are the improvements in the description when frequency or regularity information are integrated with the visual information. Integrating either frequency information or regularity information provides a significant improvement in the description. In addition, frequency information does significantly better than regularity information. This result is probably due to the relatively continuous measure of frequency compared to just three levels of orthographic regularity. The secondary recognition process of lexical access did not add much improvement for the frequency model, but did significantly improve the regularity model.

Related Work

There has been a fair amount of research evaluating the contribution of orthographic structure to letter and word perception in reading (Baron, 1978; Estes, 1978; Krueger, 1975; Massaro, 1975). More recently, McClelland and Rumelhart (1981) developed a computer simulation model of orthographic context effects in letter perception. An important feature of their model is an interaction among letter and word levels in which activation of words can modify activation of letters. This assumption contrasts with the assumed independence of visual information and orthographic context in the present simulation models. Paap, Newsome, McDonald, and Schvaneveldt (in press) have developed a simulation model that utilizes visual information to activate lexical entries in the reader's lexicon. The important feature of the Paap et al. model is the number of words activated by a given letter string. In both the McClelland and Rumelhart and the Paap et al. models, sublexical context effects are mediated by lexical activation. In the present model, these context effects result from the utilization of sublexical knowledge on the part of the reader. A critical test of these opposing views remains to be discovered.

Summary

A computer simulation of the recognition of printed letters and words was relatively successful in accounting for the reader's utilization of both visual information and orthographic structure in reading. One important feature in the simulation is the independent contributions of visual information and orthographic structure to perceptual recognition. This feature is intuitive and parsimonious since it maintains a distinction between

1980, Appendix 5.1). The performance measure comes from this experiment and a second experiment giving a total of 100 observations on each of the 200 test strings. The second experiment was identical to the first except that the target letter was given either before or after the test string. This variable had very little effect on the variables of interest.

Computer Simulation

The present general theory of reading was simulated on a PDP 11/34A computer. The simulation programs were written in C and run under the control of a UNIX 6.0 operating system.

The simulations each contain feature detection, primary recognition, and secondary recognition processes. Given the separation of these processes, it is possible to evaluate their respective contributions in the recognition of letters and words. Three classes of models were simulated and evaluated against the empirical findings of Massaro et al. (1980). In the visual model, only visual information is assumed to be utilized in recognition. In the frequency model, position-sensitive log bigram frequency is combined with visual information in perceptual recognition. In the regularity model, knowledge of legal and illegal letters and letter sequences is combined with the visual information. The visual information is represented identically in all three models. Therefore, the visual model offers a baseline for the evaluation of the contribution of orthographic structure in the other two models, and a direct comparison is possible between frequency and regularity descriptions of the reader's utilization of orthographic structure.

Visual Feature Evaluation

Features are considered to be continuous rather than binary, and each letter can be indexed by its featural similarity to every other letter. The index of similarity is taken to be proportional to the likelihood of confusing one letter for another. In order to provide an independent assessment of the featural information that is functional in the recognition of lower-case letters, Massaro et al. (1980) carried out a letter recognition experiment. A single letter was presented on each trial at a relatively dim intensity to keep overall accuracy at about 50 percent. The test letter was presented at the fixation point for a short duration and no masking stimulus was presented. Figure 5 gives the type font used in this experiment.

abcdefghijklmno
pqrstuvwxyz

Figure 5. Type font used in the experiment.

The accuracy of letter recognition and the confusion responses were taken as an index of the visual feature information available to the subject. There was a wide range of accuracy scores for the 26 letters and there were systematic errors in terms of confusing particular letters (see Massaro et al., 1980, Chapter 2, Table 2.3). These results were used to define a "goodness" value for each of the 26 letters given presentation of a particular letter of the alphabet. As an example, when the test letter "a" was presented, it was recognized correctly 37 percent of the time. In addition, it was seen as the letter "e" 14 percent of the time, and "q" 7 percent of the time. This accounts for 58 percent of the responses to the letter "a". The rest of the responses were unsystematic, being confusable by less than 5 percent.

In the simulation of the featural evaluation process, presentation of a six-letter test item produced for each test letter at each position a "goodness" value for each of the 26 letters. The goodness value assigned to each letter was equal to likelihood of that letter being recognized given presentation of the test letter. Given presentation of the test letter "a", the goodness value for "a" would be .37. The goodness value for "e" would be .14 given the presentation of "a"; "q" would be .07. All incorrect alternatives responded with less than a .05 likelihood were assumed to be zero in goodness value.

Integration-Frequency Model

The reader is assumed to store knowledge of letter occurrences in specific positions. In the model, the position-sensitive log frequency of bigram letter occurrences was stored in terms of goodness values between zero and one with the constraint that the values for all bigrams for a given position sum to one. As an example, assume that only three bigrams occurred at a given position with log frequencies of 6, 3, and 1. In this case, the respective goodness values would be .6, .3, and .1 for the three bigrams. All other bigrams at that position would be assigned a zero goodness value.

Given the visual information for each letter position, and the frequency information for each bigram position, these values were combined for each of the five pairs of adjacent letters in the six-letter string. To obtain an absolute goodness value for each possible bigram, the visual information supporting each bigram was combined with the frequency information supporting that particular bigram. These two values were multiplied for each possible bigram for each of the five positions in the six-letter string. For each bigram, a relative goodness value was computed by dividing its overall goodness by the sum of the goodness values for all of the possible bigrams at that position.

The relative goodness of each letter at each of the six letter positions in the six-letter test item was determined. Given that adjacent bigrams overlap by one letter, it was necessary to combine the information from adjacent bigrams to compute the relative goodness for letters shared by two bigrams. This procedure resulted in a relative goodness value for each confusable letter in each of the six positions in the test string.

Integration--Regularity Model

The simulation of utilizing regularity knowledge about orthographic structure was carried out in the following manner. Given presentation of a letter string, the reader first determines a candidate set of perceivable strings. A perceivable string is one that has for each letter in each position, at least, a .05 absolute visual goodness value. Therefore, only confusable letters make up the letters in the candidate set of perceivable strings. All possible perceivable strings meeting this criterion form the candidate set. As an example, given the test string "dumbap," there are six perceivable strings "dumbap," "dunbap," "dumbep," "dunbep," "dumbgp," and "dunbgp." Given a set of perceivable strings, each of the strings is evaluated for orthographic regularity. Orthographic regularity was defined in terms of rules which generated all regular (legal) vowel clusters and consonant clusters in initial, medial, and final position of a six-letter string. For each perceivable string, each letter is assigned a goodness value defining the legality of that letter in that position. The letter is assigned a goodness value representing a legal, semilegal, or illegal letter occurrence. Semilegal was used in a few cases when the legality of a given letter was not obvious according to the regularity rules. The goodness values defining the three classes of regularity were set to .9, .5, and .1 for legal, semilegal, and illegal, respectively. In the example test string "dumbap," both m and n would have an average structural goodness of one in third position.