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Continuous versus discrete information processing in pattern recognition

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Abstract

A discrete feature model (DFM) and the fuzzy logical model (FLMP) were formulated to predict the distribution of rating judgments in a pattern recognition task. The distinction was between the spoken vowels /i/ and /I/, as in *beet* and *bit*. Subjects were instructed to rate the vowel on a nine-point scale from /i/ to /I/. Two features, the first formant frequency (F_1) and the vowel duration, were orthogonally varied: The vowel /i/ has a lower (F_1) and a longer duration compared to a somewhat higher (F_1) and shorter duration for /I/. The DFM predicts that the separate features are recognized discretely, whereas the FLMP assumes that continuous information is available about each feature. Tests of these models on the observed data indicated that the continuous information assumption of the FLMP gave a significantly better description of the distribution of rating judgments.

1. Introduction

Cognitive scientists have devoted considerable effort and ingenious experiments to the question of discrete versus continuous processing. Sternberg's formalization of the additive factor method (AFM) illustrated the power and feasibility of discrete stage models (Sternberg, 1969). Other researchers documented supporting evidence in their research programs (e.g., Miller, 1988; Sanders, 1990). This work was so influential that the field of information-processing research was identified almost synonymously with the methodologies and findings of this research paradigm. As scientists, we are well aware of the power of linear models and discrete models. In addition to their attractive parsimony, they have proven successful in describing a wide range of results (Massaro and Cowan, 1993; Roberts and Sternberg, 1993).

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1.1. Stage models

Information processing is characterized by a series of successive processing stages in which each stage has some input and transforms it into an output for the succeeding stage (Palmer and Kimchi, 1986). This transformation takes some time t. In its simplest form, the discrete model assumes that the processing at a stage does not begin until the previous stage has finished. In addition, the output from a stage to the following one does not vary systematically with the time taken for the stage to process its input. For example, lowering the quality of the test letter (by adding visual noise, for example) in a memory search task would slow down the recognition stage, but it would still be transformed into a recognized letter. This output would be identical to the output given the presentation of a high-quality letter.

There appear to be four ways that discrete and continuous information and information processing can occur in stage models. Miller (1988,1990) distinguished among (a) whether the representational codes input to or output from a particular stage of processing are discrete or continuous, (b) whether the transformation accomplished at a particular stage takes place at a discrete time or gradually over time (i.e., continuously), and (c) whether the information is transmitted to the next stage at discrete times or continuously (see also Massaro and Cowan, 1993). First, the *input representation* to a stage can be continuous or discrete. Second, either of these types of input representations can be *transformed* in a discrete or continuous fashion – that is, at a given instant in time or extended over time. Third, the *transmission* of information from one stage to the next can be discrete or continuous. Finally, regardless of the type of transformation and/or transmission, the actual *output representation* of a stage can be discrete or continuous. Thus, sixteen alternatives appear to be possible.

Discrete transmission and discrete outputs are usually assumed to apply in the AFM, although they are not necessary (Sanders, 1990). Localizing the influence of an independent variable at a particular stage of processing requires the assumption of constant stage output, which is usually assumed to be unambiguous (error-free). In memory search, additive effects of test-stimulus quality and memory size can only be meaningfully interpreted if it is assumed that the output of the recognition stage does not vary with test-stimulus quality. In this case, it is natural to assume that the output of recognition must be categorical (e.g., abstract digit identity) in order to be unaffected by test-stimulus quality. Furthermore, without discrete transmission, reaction time does not necessarily equal the sum of durations of processing at all stages.

1.2. Discrete feature model (DFM)

Even the strongest advocates of discreteness would not claim that discrete processing is universal. There are many instances in which the outcome of identification is necessarily continuous or "fuzzy" because the available category labels describe some stimuli better than others (Massaro, 1987). An intermediate theoretical alternative to the discrete-continuous issue is exactly analogous to the asynchronous discrete coding (ADC) model of Miller (1982, 1988). Miller proposed that each feature of a test display is transmitted in discrete all-or-none fashion. The DFM assumes that each feature is coded in a discrete (all-or-none) fashion and, therefore, bears some similarity to earlier letter recognition models in which a given feature activates its detector with the same intensity regardless of the goodness of that feature. As an example, Gibson, 1969 hypothesized all-or-none detectors in the visual system to recognize specific features regardless of the length, density, or goodness of the feature. An all-or-none or binary feature detector means that the feature is detected as being either present or absent (or having one of two values).

The DFM makes it possible for a perceptual representation to appear continuous even though each feature is encoded in a discrete manner. A letter, for example, would necessarily have several features whose outputs might not necessarily be consistent with one another. With two features, a letter might be consistent with 0, 1, or 2 features. Thus there would be potentially 3 rather than just 2 levels of information about this letter even though information about each separable feature of the letter is discrete. The DFM is powerful because it is not necessarily inconsistent with either discrete or continuous results. Discrete codes would be observed when just a single feature must be processed whereas continuous performance would be representative of processing multiple features. An alternative model assumes that information about a single feature is continuous.

1.3. Fuzzy logical model of perception (FLMP)

The fuzzy logical model of perception (FLMP) assumes feature evaluation, feature integration, and decision (Oden and Massaro, 1978). Continuously-valued features are evaluated, integrated, and matched against prototype descriptions in memory, and a response is made on the basis of the relative goodness-of-match of the stimulus information with the relevant prototype descriptions. Thus, the FLMP differs from the DFM in terms of having continuous rather than discrete information about the features. Information about each feature is represented in terms of truth values from fuzzy logic because they provide a natural representation of the degree-of-match. Fuzzy truth values lie between zero and one, corresponding to a propositionbeing completely false and completely true. With two contrasting alternatives, the value 0.5 corresponds to a completely ambiguous situation, whereas 0.7 would be more true than false, and so on. Fuzzy truth values, therefore, not only can represent different kinds of information, they can represent continuous rather than just discrete information.

1.4. Nature of information output

The goal of the present research is to test whether single features are encoded discretely as assumed by the DFM or continuously as assumed by the FLMP. Consider the six level *c–e* continuum illustrated in Fig. 1. It can be safely argued

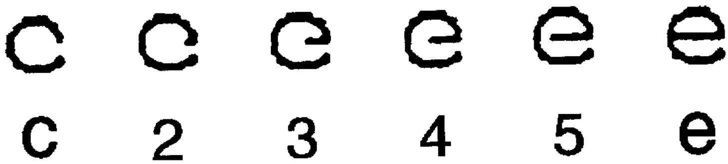

Fig. 1. A continuum of 6 letters varying between a prototypical *c* and a prototypical *e*.

that only a single feature distinguishes these letters. Thus, the DFM can be interpreted to predict that recognition of these letters should be characterized by a discrete perception model. Although discrete judgments do not permit a test between these theories, rating judgments can be analyzed to distinguish between them. In rating judgments, subjects are asked to rate the stimulus in terms of the degree to which it falls between two prototypical extremes, e.g., a good *c* or a good *e*. An important question is how the mean rating responses are expected to differ as a function of the position along the stimulus continuum. According to the DFM, a given stimulus produces an information state *c* with probability P_c and an information state *e* with probability $1 - P_c$. Perception is discrete and probabilistic, and a stimulus produces the information state *c* to the extent that it is towards the *c* end of the continuum. We can also expect a distribution of rating judgments given each information state because of random variability in the perceptual, memory, or response systems. The distribution of rating responses to a given stimulus will actually be a mixture of ratings generated by two distributions, corresponding to *c* and *e* information states. The proportion of ratings generated from the distribution of *c* ratings will increase with increases in P_c. Continuous changes in the mean rating response can occur with continuous changes along the *c*–*e* continuum, even though perception is discrete.

The FLMP assumes that readers perceive the degree to which a test letter resembles each alternative. The FLMP predicts a systematic and continuous change in the distribution of information states across the six test letters. The information state given a stimulus towards the *c* end of the continuum will be more *c*-like than that of a neighboring stimulus towards the *e* side of the continuum. The FLMP also predicts that mean rating responses change continuously with changes along the stimulus continuum.

The discrete and continuous perception models can make similar predictions for the mean rating judgments. Thus, the mean rating judgments alone are not capable of testing between the two models. The models, however, can be distinguished on the basis of the distribution of rating responses because the distribution of rating responses is predicted to differ for the two models. For example, for an ambiguous stimulus in the middle of the *c*–*e* continuum, the discrete model would predict a bimodal distribution with a central trough, whereas the continuous model would predict a distribution with a single peak.

When the distributions of rating judgments are analyzed, the results favor the continuous over the discrete model. There is evidence for continuous recognition of speech (voicing, voice onset time, and vowel quality, Massaro and Cohen, 1983), musical consonance (Hary, 1984), and letter features (Massaro, in press).

The goal in this paper is to extend this type of test to speech stimuli that vary along two auditory dimensions. There are several justifications for an additional test in a situation with two varying dimensions. It is important to know if our conclusions reached in single-factor studies can be extended to a two-factor study. It might be the case that perception at the feature level becomes discrete when two or more features are varied in a stimulus. The two-factor study probably requires a combining or integration process that is not necessary in the single-factor situation. The addition of this integration process might limit the perceiver to only discrete information about each feature. The more complex experimental situation also allows us to test a more complex discrete feature model. It warrants empirical test because the more complex model might give accurate predictions even though a simpler version has already been falsified.

The test situation involved the distinction between the spoken vowels /i/ and /I/, as in *beet* and *bit*. The two features orthogonally varied were the first formant frequency (F_1) and the vowel duration. The F_1 is higher in /I/ than in /i/, and /i/ tends to be longer in duration. Subjects were instructed to rate the stimulus to the degree to which it falls between the two alternatives – i.e., a good /I/ or a good /i/. The distribution of rating judgments for each subject were tested against formal predictions of the DFM and the FLMP.

2. Method

2.1. Subjects

Seventeen native speakers (11 females and 6 males) of American English participated in this experiment. Their average age was 20.8 years. All were students from the University of California, Santa Cruz. They reported having normal hearing, and normal or corrected-to-normal vision. The subjects were paid six dollars for their participation. All subjects were unfamiliar with the specific goals of the study.

2.2. Apparatus and materials

The test vowels were made from synthetic audible speech using the Klatt (1980) software synthesis program. The stimuli were variations of the vowels /I/ and /i/. We first generated eleven 300 ms vowels. These vowels differed only in the first formant (F_1), which varied from 310 to 400 Hz in 9 Hz steps. In the experiment proper, the F_1 values were 310, 328, 346, 364, 382, and 400 Hz. The other formants were fixed: F_2 at 2000, F_3 at 2815, and F_0 at 120. We varied only F_1, rather than F_1 and F_2, because we interpreted F_1 as a single feature in the context of the DFM. The bandwidths were 50, 150, and 270 Hz for the first three formants, respectively. The stimuli also varied in duration. Eleven durations were made: 20, 30, 45, 65, 80, 100, 125, 150, 180, 210, and 245 ms. The 6 durations used in the experiment proper were 20, 45, 80, 125, 180, and 245 ms. To ensure a valid test between the FLMP and DFM, no other aspect of the test stimulus was varied.

There were two groups of subjects that differed with respect to their introductions to the experiments. Nine of the subjects had the 11 step F_1 continuum played twice as an example of the vowels going from /I/ to /i/. The duration was held constant at 300 ms. The other eight subjects had the 11 step duration continuum played twice as an example of the vowels going form /I/ to /i/. The F_1 was held constant at 355 Hz.

2.3. Design and procedure

Vowel duration and vowel quality were manipulated in a factorial design. There were 6 possible durations and 6 possible F_1 formants. Each of these 36 trial types was presented once in every block of 36 trials. There were 8 blocks of trials per session and a total of 3 sessions. This design gives a total of 24 rating responses per subject for each vowel. Unknown to the subjects, there were also 10 unanalyzed practice trials before each experimental session.

A Silicon Graphics Inc. Crimson-VGX computer was used to control the experiment. The stimuli were presented using a Vigra MMI-210 audio board at a 16K sampling rate. Responses were made using TVI-950 terminal keyboards connected by serial lines to the SGI computer.

Subjects were instructed to rate each stimulus indicating where on a 9-point /I/ to /i/ scale the vowel fell. "In the experiment, you will hear a vowel on each trial. Your task will be rate where on a nine point scale from /I/ to /i/ you perceive the vowel to be. You will make your response using only these 9 buttons EE-1, 2, 3, 4, 5, 6, 7, 8, IH-9 on the top row of your keyboard. The EE button would be used to indicate the best EE, and the IH button would be used to indicate the best IH. The other seven buttons would be used to indicate intermediate degrees of the vowel between these extremes. For example, the 3 button would be used for a vowel perceived to be a fairly good EE, but not as good as EE-1 or 2. The 7 button would be used for a vowel perceived to be a fairly good IH, but not as good as IH-9 or 8 and so on for the other buttons. The 5 button would be used in the case a vowel which falls exactly in the center between EE and IH."

The experimental stimuli were presented to the subjects over SONY MDR-V6 headphones. The loudness level of the auditory stimuli was 68.4 dB-A (slow). The measurement was done with the sound level meter (B&K 2231, with a Type 4133 microphone and a type 4153 B&K artificial ear. The playback amplitude of each vowel was adjusted to make it equivalent for each test vowel.

Up to four subjects could be tested simultaneously in individual sound-attenuated rooms. These rooms were each illuminated by two 60 Watt incandescent bulbs in a frosted glass ceiling fixture. The experiment was subject-driven, i.e. a next trial would only occur after all of the simultaneously tested subjects had responded to the previous trial.

3. Results

3.1. Mean rating judgments

Subjects' response ratings were recorded for each stimulus. In addition to the raw ratings, a mean /I/-ness rating was computed. The ratings were transformed to a 0–1 /I/-ness scale by subtracting 1 and dividing by 8. The mean observed /I/-ness was computed for each subject by pooling across all 24 experimental trials for each condition. Fig. 2 shows the mean rated IH-ness as a function of duration and F_1 averaged across the formant and duration demonstration groups. The rating of /I/-ness decreased with decreases in the F_1 value and with increases in vowel duration. In addition, increases in vowel duration enhanced the discriminability of the F_1 values. Finally, although not shown in Fig. 2, the two different demonstrations of vowel changes before the experiment influenced performance. Subjects were more sensitive to the independent variable that was systematically varied during the demonstration. All of these differences were statistically significant ($p < 0.001$).

3.2. Model tests against distributions of ratings

Subjects made their rating judgments by hitting one of 9 keys on the nine-point scale from /i/ to /I/. For each subject, the proportion of rating judgments in each of these rating categories (bins) was computed. In all cases, the models were fit to the proportions of judgments in each of the 9 rating bins. A number of discrete and continuous models were tested against the results. Each model was formulated mathematically and fit to the results of each subject. The free parame-

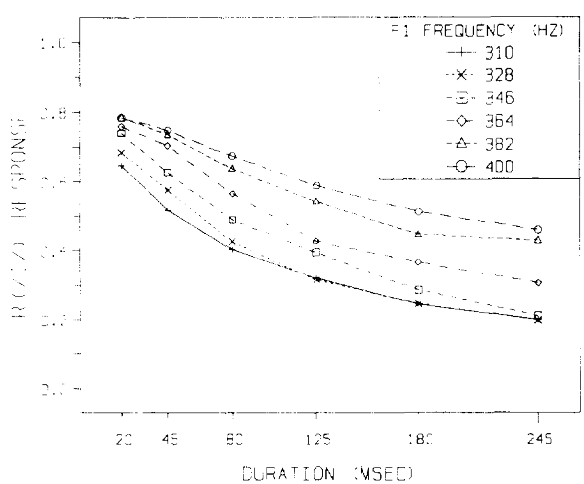

Fig. 2. Mean rated /I/-ness as a function of the duration of the test vowel; the F_1 formant frequency is the curve parameter.

ters were estimated to minimize the squared differences between the predicted and observed values, using the minimization program STEPIT (Chandler, 1969). The goodness-of-fit of a model to a subject's results is given by the root mean squared deviation (RMSD) between predicted and observed values. Models are compared by ANOVAs on these RMSD values.

Although a number of different instantiations of the FLMP and DFM were tested against the results, we present only a single representative comparison. In all cases, when these two models were made as comparable as possible with a similar number of free parameters, the continuous model gave a significantly better description than the discrete model.

3.3. Test of the FLMP

The three operations of the FLMP can be formalized mathematically. Feature evaluation gives the degree to which each characteristic supports the presence of a particular prototype feature. The physical input is transformed to a psychological value, and is represented in lowercase, e.g., F_i would be transformed to f_i, the degree to which the formant value supports the formant feature of the alternative /I/. With just two alternatives, /I/ and /i/, we can make the simplifying assumption that the degree to which the formant value supports the alternative /i/ is $1 - f_i$. Feature evaluation would occur analogously for the duration feature, D_j.

Feature integration consists of a multiplicative combination of feature values supporting a given alternative. If f_i and d_j are the values supporting alternative /I/, then the total support, $S(/\mathrm{I}/)$, for the alternative /I/ would be given by

$$S(/\mathrm{I}/|F_i, D_j) = f_i d_j. \tag{1}$$

The third operation gives the relative degree of support for each of the test alternatives. In this case, the rating of an /I/ response given F_i, D_j is equal to the total support for /I/ divided by the sum of $S(/\mathrm{I}/)$ and $S(/\mathrm{i}/)$.

$$R(/\mathrm{I}/|F_i, D_j) = \frac{S(/\mathrm{I}/)}{S(/\mathrm{I}/) + S(/\mathrm{i}/)} = \frac{f_i d_j}{\left[f_i d_j + (1 - f_i)(1 - d_j)\right]}. \tag{2}$$

Central to the FLMP is the amount of support of each of the two features for each of the two alternatives. A complicating factor is that cue value of the F_1 cue was also dependent on vowel duration, so that F_1 was more informative with longer durations. To build this factor into the cue value for F_1, the cue value was assumed to move away from 0.5 towards an asymptotic value with increases in vowel duration. That is, an F_1 value supporting /I/ has some optimal support at a given duration, and shorter durations give some value between this value and the ambiguous value 0.5. It was assumed that the F_1 feature value supporting the alternative /I/ was a weighted average of its asymptotic support and 0.5.

$$f_{id}(/\mathrm{I}/) = w_d afi(/\mathrm{I}/) + (1 - w_d)0.5, \tag{3}$$

where f_{id} is the cue value of a particular F_1 at a given duration, *afi* is the asymptotic support for that F_1, and w_d is the weight given the asymptotic support. The support for /i/ would simply be one minus the support for /I/, given by Eq. (3).

The integration rule of the FLMP was used to combine the F_1 and duration information to predict the distribution of ratings to the 36 different vowels. The FLMP rating model assumes that there is a normal distribution of truth values for each feature. That is, a given level of a given feature generates a distribution of feature values. Thus, each cue level has a unique mean and a standard deviation. In this formulation, there are six unique means for the six levels of duration, six asymptotic values for the six levels of F_1, and 6 weights on the cue values for F_1 (as a function of duration). Normally, there would be an additional 12 free parameters necessary for the standard deviations. However, we assumed that the standard deviation of a feature distribution was simply a polynomial function of its truth value. Previous results of single-factor experiments indicated that the standard deviation of the distribution of ratings tends to decrease as the truth value becomes less ambiguous (moves away from 0.5 towards 0 or 1). This third-order polynomial required 4 free parameters. Therefore, the implementation of the continuous FLMP requires $6 + 6 + 6 + 4 = 22$ free parameters. Given these values, the 36 rating distributions corresponding to the 36 different vowels can be computed directly by convolving the two feature distributions through the integration rule of the FLMP.

The computation of the fuzzy logical integration of the two feature distributions is done as follows. Each of the 9 rating bins is set to 0. Consider all possible joint occurrences of the F_1 feature falling in bin j and the duration feature falling in bin k. For each jk combination, we take the center values of the bins and combine them according to the FLMP. The resulting value tells us in which bin of the resultant distribution the identification will fall. To that bin we then add the product of the areas of the two bins j and k, which gives the probability of the joint occurrence of the F_1 feature falling in bin j and the duration feature falling in bin k. This entire process is repeated for each possible combination of stimulus levels for the two features.

This implementation of the FLMP was fit to the observed distributions of each of the individual subjects. The FLMP described the results with an average RMSD of 0.072. Fig. 3, Figs. 4 and 5 give the observed distributions of ratings for three typical subjects. As can be seen in the figure, the FLMP does a fairly good job of describing the results. The predicted lines tend to follow the trends in the observed points. We will contrast this fit with the fit of the discrete model as implemented in the DFM.

3.4. Test of the DFM

The DFM is formalized to be as analogous to the FLMP as possible, with the primary exception of continuous versus discrete feature information. Thus feature evaluation, feature integration, and decision are specified. Features are evaluated

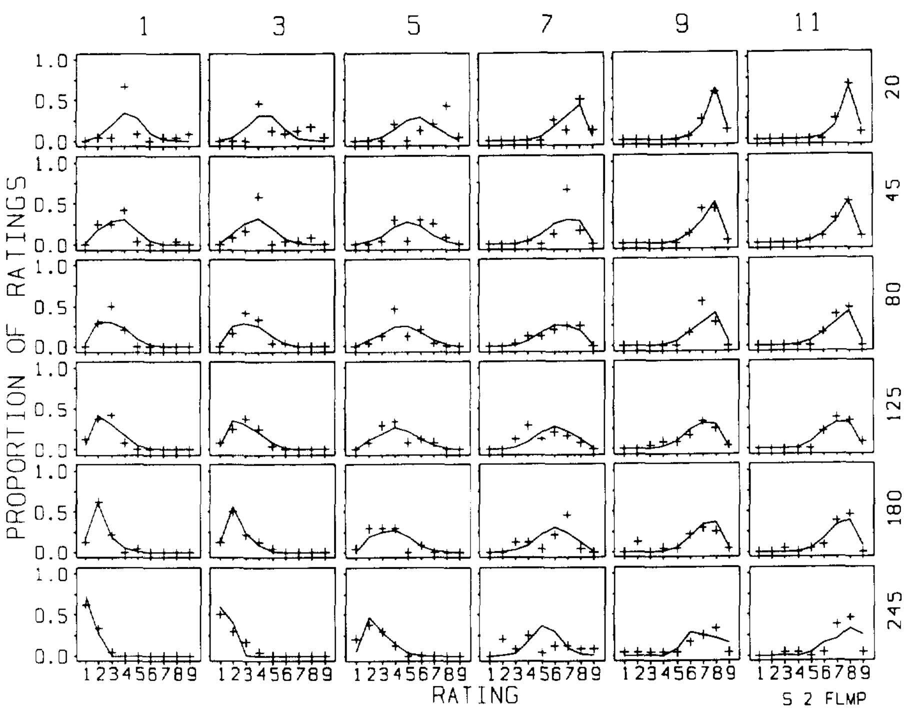

Fig. 3. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 2 and predictions of the FLMP.

as being present or absent which represents the discreteness property. Feature evaluation provides information about whether each feature in the test vowel matches one alternative or the other. Feature integration consists of counting the number of matching features for each alternative. In the decision operation, the count of feature matches for each competing prototype is evaluated relative to the sum of the counts for all competing prototypes. This relative goodness-of-match gives the rating judgment indicating the degree to which the test vowel matches /I/.

The integration of the features is assumed to be the sum of the number of feature matches. In this case with two varying features, the outcome can be 0, 1, or 2. If M(/I/) and M(/i/) correspond to the number of matches to the /I/ and /i/ alternatives, respectively, the decision operation determines their relative merit to produce a rating response

$$R(/\mathrm{I}/) = \frac{M(/\mathrm{I}/)}{M(/\mathrm{I}/) + M(/\mathrm{i}/)}, \tag{4}$$

where $M(/\mathrm{I}/)$ can be 0, 1 or 2, depending on whether the test stimulus is evaluated as having 0, 1 or both of the /I/ features. Because /I/ and /i/ are defined as differing on both features, $M(/\mathrm{i}/) = 2 - M(/\mathrm{I}/)$.

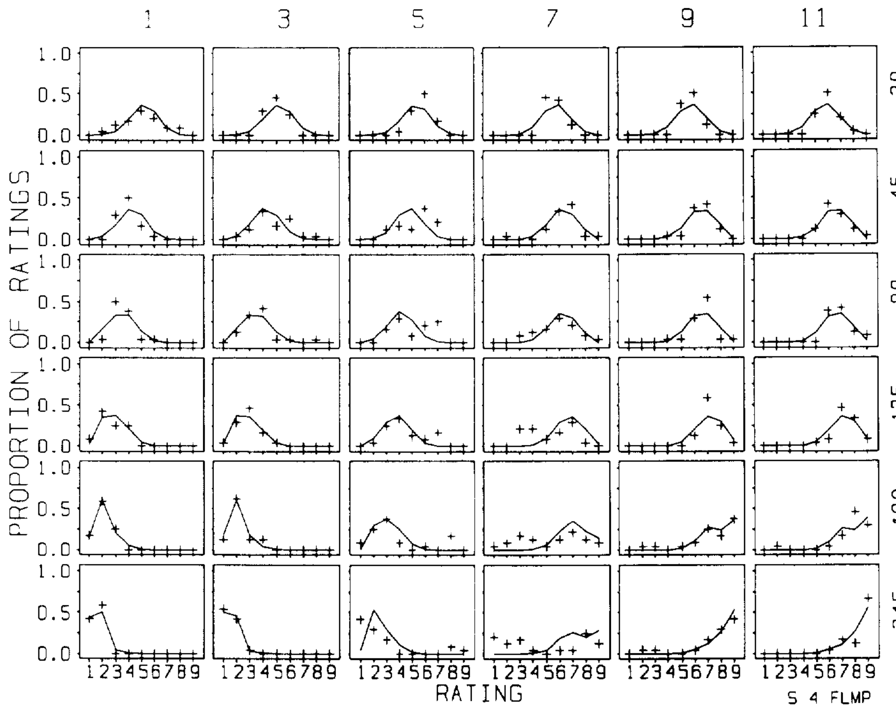

Fig. 4. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 4 and predictions of the FLMP.

To derive the predictions for the rating judgments, it is necessary to determine the likelihood of obtaining the different outcomes of 0, 1, or 2 feature matches. Table 1 gives the probabilities of the four possible outcomes of the feature evaluation process. The probability f_i is defined as the probability of evaluating the formant feature as matching /I/. The probability d_j is defined as the probability of evaluating the duration feature as matching /I/. Suppose that we have values for the f_i and the d_j. As can be seen in Table 1, both the F_1 and duration features will match the alternative /I/ with probability $f_i d_j$. When this occurs, it is assumed that the rating comes from a distribution near the /I/ end of the rating scale. Similarly, both the F_1 and duration features will match the alternative /i/ with probability $(1-f_i)(1-d_j)$. When this occurs, it is assumed that the rating comes from a distribution near the /i/ end of the rating scale. The final case is when only one of the features matches, and the rating will come from somewhere in the middle of the rating scale. This case is given by sum of the lower left and upper right cells in Table 1. Thus, the overall distribution of rating judgments is predicted to be a mixture from three separate distributions, occurring with the probabilities given by Table 1.

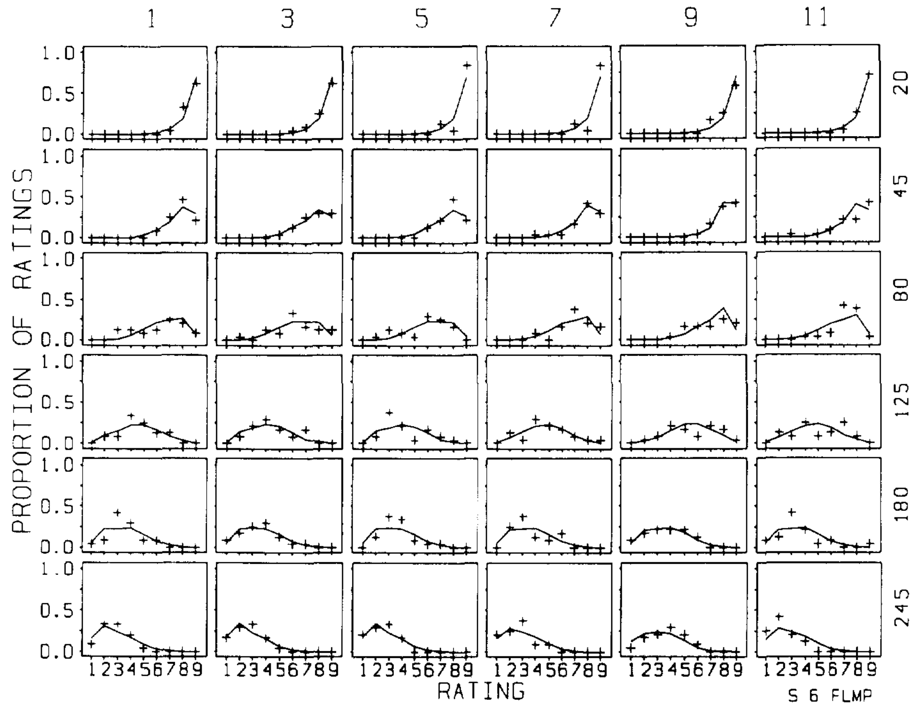

Fig. 5. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 6 and predictions of the FLMP.

If subjects actually perceived discretely, they might object to being asked to make continuous rating judgments. However, as in most research, they would probably attempt to comply. In the case of two independent features, the subject would choose a rating toward the /I/ end of the response scale for the case in which both features match /I/, toward the /i/ end for the case in which both features match /i/, and somewhere in the middle of the response scale for the case in which one feature matches /I/ and one feature matches /i/. Although there would be only three possible information states, there would probably be a

Table 1
The probabilities of the four possible outcomes of the feature evaluation process for the DFM. The term /I/-match means the designated feature matches the prototype for /I/ and not for /i/.

Formant	Duration	
	/I/-match	/i/-match
/I/-match	$f_i d_j$	$f_i(1-d_j)$
/i/-match	$(1\text{-}f_i)d_j$	$(1-f_i)(1-d_j)$

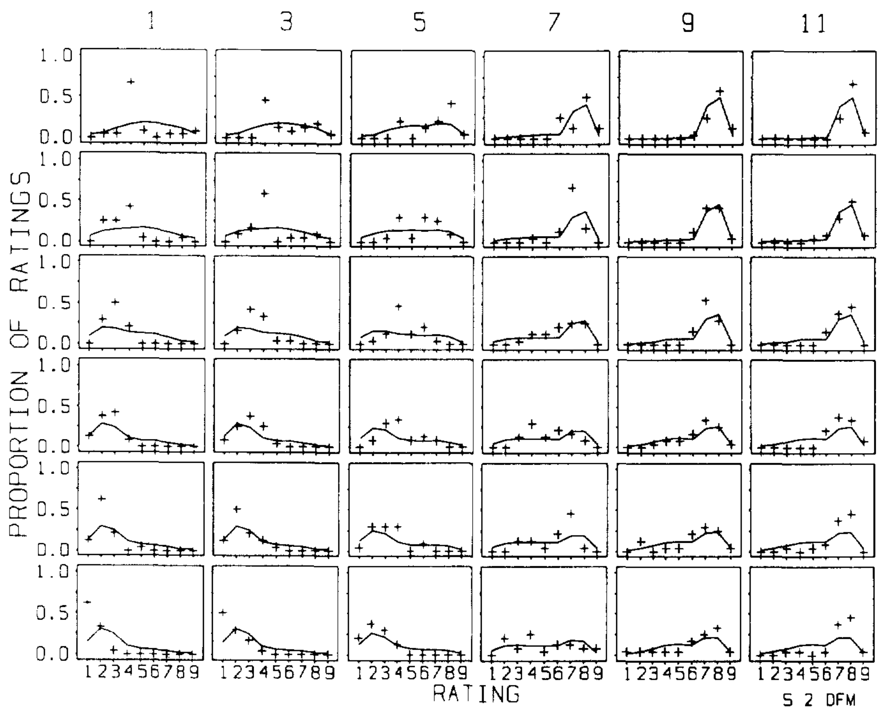

Fig. 6. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 2 and predictions of the DFM.

larger number of different ratings. A subject might not remember exactly the rating previously given for one of the three states. Subjects may not remember exactly what rating they gave when both features matched /I/, for example. Thus, the same information state would receive somewhat different ratings on successive trials. This variability in the subject's memory of the ratings, would produce a distribution of rating responses for each of the two percepts. Furthermore, given the rating task, subjects might actually generate additional variability in their ratings if their percepts are discrete and they feel that they are expected to make a range of rating responses.

This implementation of the DFM requires 6 f_i values, 6 d_j values, and 6 w_d values to determine the likelihood of entering each of the 3 information states for each test vowel. Three free parameters are also necessary for the three means of these states and three more for their standard deviations. Thus, a total of 24 free parameters are necessary, two more than needed for the predictions of the FLMP.

The fit of the DFM produced an average RMSD of 0.084, significantly larger than the RMSD of 0.072 for the FLMP, $F(1,16) = 4.83$, $p < 0.05$. Fig. 6, Figs. 7 and 8 give the DFM's predicted distributions of ratings for the same three subjects shown in Fig. 3, Figs. 4 and 5. As can be seen in the figure, this implementation of

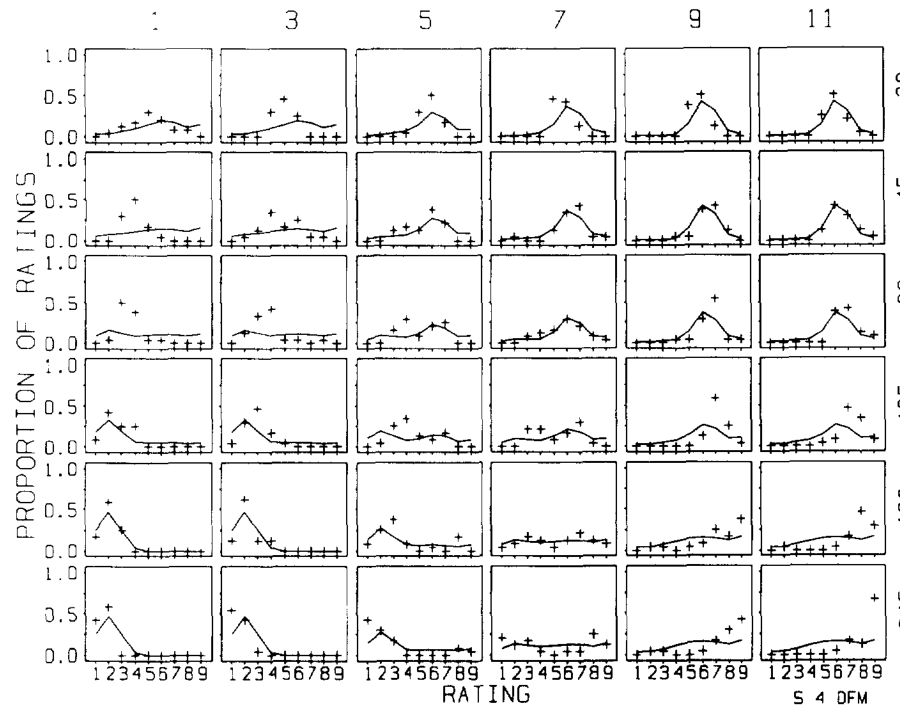

Fig. 7. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 4 and predictions of the DFM.

the DFM gave a poorer description of the distribution of rating judgments than did the FLMP. Although the differences in RMSDs were not large, the figures show that the DFM was not able to describe significant aspects of the distributions that were well described by the FLMP.

4. Discussion

The results of the present experiment demonstrated that there is continuous information available about each feature. The integration of several features also provides continuous information about the degree to which a given alternative is present. This type of a continuous output representation is not a problem for the information processing approach because continuous outputs are not necessarily incompatible with serially arranged stages of processing that are separately influenced. In the FLMP, fuzzy information from each source of information is evaluated independently of other sources. This continuous information is transmitted to an integration stage of processing in which fuzzy information from several sources is combined. The outcome of the integration stage, also fuzzy or continu-

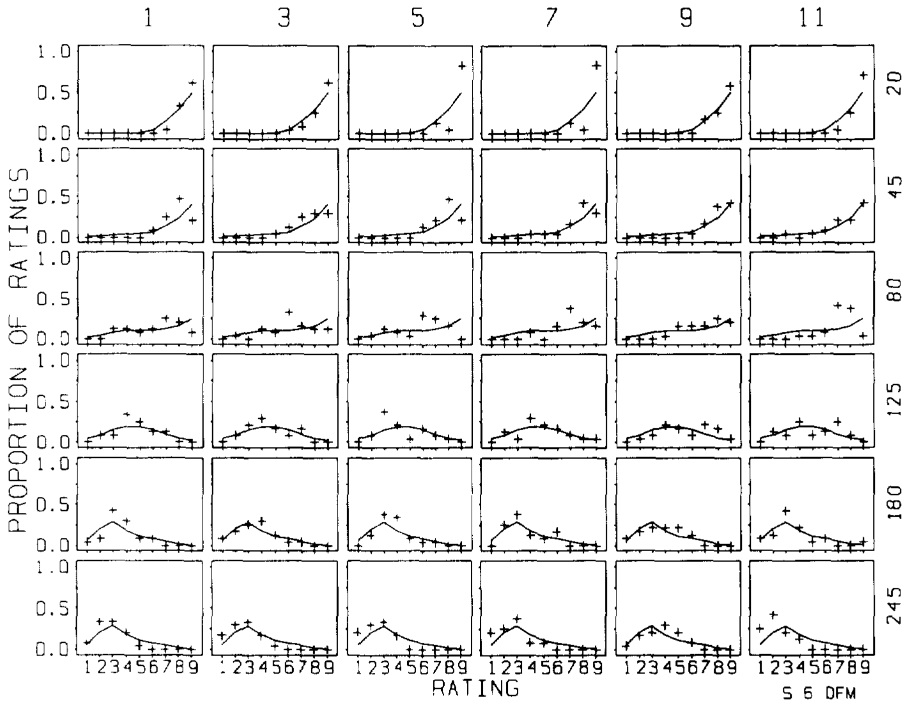

Fig. 8. The observed and predicted distribution of rating judgments across the 9 rating categories as a function of the duration of the test vowel and the F_1 formant frequency. Results for subject 6 and predictions of the DFM.

ous, is transmitted to a decision stage in which the relative goodness of match of an alternative is determined. The stages in the FLMP are sequential and can be influenced independently of one another – even though their outputs have a continuous output representation (Massaro, 1987).

The FLMP differs from the DFM with respect to two of the three processes: continuous versus binary output of the evaluation process; multiplicative versus additive integration; and same decision rule. In both cases, the FLMP presumes processes that are more efficient or optimal than those assumed by the DFM (Massaro, in press). It is obvious that having continuous information is an advantage over being limited to discrete information. Knowing how much an item costs is more informative than simply knowing whether or not the item is expensive. Although not as intuitive, it has been proven that multiplying two sources of information in the FLMP is more optimal than simply adding the sources in the DFM (Massaro, 1987, Section 10.3).

Our experimental results demonstrate the existence of a continuous output representation. Perceivers in our task had plenty of time to make their judgment, however, and it might be argued that this representation might not be made available to rapid responses. As indicated in several of the papers of this special issue, there is still a good deal of disagreement about whether perceptual processes make continuous information available to response processes. One might also argue against continuous transmission of information from one stage to the next even if the output of a stage is continuous. In this case, the continuous representation would be passed forward at a discrete moment in time. There is nothing in our present research that addresses this issue.

Some hint of continuous processing and transmission comes from the present study in which vowel duration, not only provided a cue to vowel identity but also influenced the resolution of the formant cue. Increases in duration increase resolution of the formant cue. One might argue that the transformation of formant cue occurred continuously in the evaluation stage and was transmitted continuously to the integration stage. However, it is possible that the continuous information from evaluation was not transmitted forward to integration until the offset of the vowel at which time it was transmitted in a discrete fashion. Although this remains a logical possibility, it seems highly unlikely to us. If a masking stimulus followed the test vowel after some silent period, we would expect performance to improve with increases in the silent period. This masking function would illustrate that perceivers do not necessarily transmit the information from the evaluation stage at the offset of the test vowel.

In summary, the FLMP appears to describe the processing involved in feature analysis and identification stages that are assumed in most information processing models. If the FLMP is an accurate representation for perceptual processing in most situations, then general models must account for processing when continuous information is available from these initial stages of processing. A model might always assume that this continuous information does not influence subsequent processing stages. Although this might be the case in some situations, we doubt that it can be a general phenomenon. The extant challenge is to delineate those situations in which continuous information is functional in perception and action.

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