Form recognition: Individual strategies in multivariate cue utilization¹

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Twenty-five Ss were each presented 1,250 trials in a form-recognition task requiring S to find a form among 25 other forms on each trial. Fifty different eight-sided randomly derived polygons were used as stimuli, each presented in 25 different problems. Factors based on physical measures of the stimuli were correlated with observed latencies using multiple regression to assess cue-utilization strategies, while beta-weight profiles and intercorrelations of the Ss' predicted latencies were used as indices of individual differences. Multiple correlations of physical-factor scores with observed latencies accounted for a significant proportion of the variance for all Ss, while between-S correlations of predicted latencies were never below .90. By all criteria employed, use of stimulus information was highly consistent among Ss. Replication of the experiment for one S revealed good reliability and nearly identical strategies.

Successful application of psychophysical methodology to the problems of form perception, long-deterred by lack of techniques for multivariate stimulus specification, has recently engendered research to determine appropriate methods of assessing stimulus information. A review of the literature on the development of a metric for visual-form perception indicated that the fundamental problem was still largely unsolved (Michels & Zusne, 1965). Brown and Owen (1967), in a systematic effort to study the measurement and sampling of randomly derived polygons, developed an exploratory metric for a psychophysics of form with a methodology emphasizing the multidimensionality of a form stimulus and providing a multivariate statistical approach for the description of a given set of stimuli. They used measures of side, angular, radial, perimeter, and areal variability to abstract a structure of orthogonal factors so that forms were represented along a small number of factored dimensions rather than along the comparatively large number of original physical measures. Owen and Brown (1970a, b), using the measurement system, were able to account for significant amounts of variance in both visual- and tactual-discrimination tasks as well as in

complexity judgments. Stenson (1966) successfully used a similar predictive scheme for complexity judgments of random polygons. The factor analytic structure accounted for a large proportion of both the measured physical variance in stimulus attributes and the response variance in judgment and choice tasks.

Given that a relatively appropriate multivariate specification of stimuli has been developed and that psychophysical equations have been written to account for performance variation, the next question concerns the generality of the equations obtained from these procedures. An equation is applicable to a group of Ss, i.e., represents the group strategy, only to the extent that individual S's strategies are similar. Individual differences in pattern perception have been found in such divergent areas as demonstrating the use of features of schematic faces in judgments of intelligence (Rodwan & Hake, 1964) and indicating the existence of two points of view in similarity judgments of a factorially constructed sample of forms (Torgerson, 1965). Silver, Landis, and Messick (1966) also found individual differences in cue utilization for a sample of forms in a multidimensional scaling task. Stenson (1966) found that, although there was high correlation among Ss' complexity judgments, there was a suggestion of individual differences since some Ss seemed to use certain physical cues to a greater extent than did other Ss. These findings point out the potential significance of different cue-utilization strategies in form perception. Assessment of individual differences in the use of stimulus information must be made before the generality of any psychophysical model for form perception can be determined. That is to say, a low proportion of performance variance accounted for by a group equation may indicate that the particular model is inappropriate, or that Ss were using the measured cues differently, or both.

Determining the extent of individual differences in form perception involves ascertaining what stimulus information or weighted combination of cues accounts for response variation both within and between Ss. One method that lends itself to this type of analysis is the use of multiple regression to obtain the weighted

combination of cues (Attneave, 1957). The use of one regression equation based on the averaged data of many Ss would lend support to the notion that perception of such a multivariate stimulus as form can be accounted for and, perhaps, predicted by a weighted combination of univariate features. However, if variation in an individual S's data is not well accounted for by a group regression equation, the focus of research must necessarily shift to groups of individuals that respond similarly or, if individuals differ continuously, their position on the relevant continua must be specified.

Study of cue utilization by individuals requires that S be allowed alternative strategies and a task difficult enough to generate variability in the response indicant so that such strategies can be recovered by analysis. A task permitting single-form analysis was desired since a study by Owen and Brown (in press, b), using a six-choice oddity problem, indicated that there are, as yet, unsolved problems in accounting for discrimination latencies with differences in pairs of factor scores. The present study employed a more sophisticated version of a recognition task employed by Fitts, Weinstein, Rappaport, Anderson, and Leonard (1956) and stimuli described using the metric developed by Brown and Owen (1967). The assumption was made that individual differences in utilization of information in a form-recognition task would be reflected by differing within-S multiple-regression equations as well as by comparison of individually predicted latencies with latencies predicted by the group-regression equation.

METHOD

Subjects

Twenty-five male students at Ohio State University participated in the experiment as part of a course requirement in introductory psychology. In order to obtain reliability information, one S repeated the entire experiment twice, with 2 months elapsing between replications.

Stimuli

Fifty forms were sampled from the 200 eight-sided figures generated by Brown and Owen (1967), according to slightly amended Attneave and Arnoult (1956)

Fig. 1. An example of the 1,250 recognition problems.

Method I rules. Number of sides and area were held constant to allow Ss to use more subtle stimulus information. Eight-sided figures were chosen since previous discrimination experiments with Method I forms suggested an optimal level of information processing at that level of complexity (Brown, Hitchcock, & Michels, 1963; Owen & Brown, in press, a). Fifty 5 by 5 matrices were randomly generated, two at a time, so that every form appeared in every position once and only once. The 50 matrices, as well as the 50 individual forms, were then photographed to provide slides.

Apparatus and Procedure

The display manipulandum consisted of a 20 x 20 in. black grid, with 25 3-in. square holes spaced $\frac{1}{2}$ in. apart on all sides, forming a 5 by 5 matrix. A clear Plexiglas door behind each of the holes touched a contact when pressed and returned to its original position when released. For each trial, the recognition slide was projected onto a 3-in. square rear projection screen immediately above the matrix grid, where it remained for 1.5 sec, after which the matrix slide was projected onto a screen behind the grid, and a 1/100-sec digital timer was activated. Figure 1 shows a sample recognition slide above a matrix slide as a problem appeared to S. S initiated the trial by controlling presentation of the recognition form and was instructed to press the door in front of the form that matched the recognition form as quickly and accurately as possible, using his preferred hand. A correction procedure was used so that a correct choice stopped the timer and removed both the

Table 1
Multiple Correlation of 10 Factors with Observed Latencies for Each S ($R_{mult.}$) and Correlations of Each S with Group Latencies for Observed (R_{O_S, O_G}) and Predicted (R_{P_S, P_G}) Latencies

S	$R_{mult.}$	R_{O_S, O_G}	R_{P_S, P_G}
1	.64	.58	.92
2	.73	.68	.93
3	.79	.71	.91
4	.76	.69	.91
5	.66	.63	.96
6	.67	.62	.92
7	.63	.61	.97
8	.72	.68	.94
9	.69	.66	.96
10	.65	.64	.98
11	.65	.62	.95
12	.65	.62	.95
13	.69	.66	.94
14	.63	.60	.94
15	.71	.67	.94
16	.64	.62	.98
17	.76	.74	.98
18	.77	.74	.96
19	.61	.56	.92
20	.65	.63	.97
21	.69	.65	.95
22	.63	.57	.90
23	.71	.64	.91
24	.72	.66	.92
25	.65	.60	.92
25R	.76	.75	.98
G	.77		

R = Replication; G = Group

recognition and matrix forms from the screens, while neither was terminated by an error. Latency and number of errors were recorded.

For each S, the sequence of trials was determined randomly by a computer program, with the restriction that every form appeared in each session of 50 trials. Approximately 250 trials were completed in a daily 1-h period, the entire 1,250 problems being finished in 5 to 6 days.

RESULTS

Means and medians were computed for each form from the latencies for the 25 problems in which it appeared as the recognition form. Because interest was centered on relative problem difficulty, rather than on whether or not an S was a quick or slow responder, form mean and median latencies were standardized within S about the grand mean of the 50 forms for use in all subsequent analyses. Since there were no gross differences between the mean and median data, only analyses using means were reported. All further references to latencies, either predicted or observed, should be considered standardized latencies. Errors were too rare to consider analyzing.

The independent variables were 10 orthogonally rotated factors obtained by

principal-components factorization of 80 geometric and statistical measures of 200 eight-sided forms. Factor scores of forms were standardized within the subsample of 50 forms before being used in regression analyses so that standardized regression weights would be obtained.

Analysis of Individual Ss

A standardized regression equation, using factor scores to account for variation in form mean latencies, was obtained for each S. The multiple correlation for each equation is presented in Table 1. The F test for the significance of a multiple correlation (MS Regression/MS Residual, $df = 10/39$) showed that all regression equations accounted for a significant proportion of the variance ($p < .05$). Figure 2 shows examples of beta-weight profiles for five Ss chosen at random. A high negative or positive weight for a given factor indicated a high degree of cue utilization, the sign being relative to arbitrary factor valences.

Using the beta-weights resulting from the multiple-regression analysis, predicted values of standardized latencies were generated for each S as a sum of the weighted factor scores. Correlations between Ss based on predicted latencies were then computed in order to compare the similarity of regression equations (Naylor & Schenck, 1966). These correlations ranged between .72 and .97.

Principal-components factor analyses performed on the observed and the predicted latency data revealed essentially one factor in both cases. Two indices support the conclusion of inter-S homogeneity: (1) The eigenvalues obtained from the factor analyses fell below unity

Fig. 2. Examples of beta-weight profiles for 5 Ss chosen at random from the 25 Ss.

Fig. 3. Beta-weight profiles for two Ss with observed latencies correlated .84 and predicted latencies correlated .95.

Fig. 4. Beta-weight profiles for two Ss with observed latencies correlated .49 and predicted latencies correlated .97.

after the first factor; and (2) the proportion of variance accounted for by the first factor extracted was 70% for the observed latencies and 89% for the predicted latencies, while the second factor accounted for only 4% and 3%, respectively.

Figure 3 shows the beta-weight profiles of two Ss whose observed latencies correlated .84 and whose predicted latencies correlated .95. Figure 4 shows the beta-weight profiles of two Ss whose observed latencies correlated .49 but whose predicted latencies correlated .97. These comparisons show similarity between profiles of beta-weights for the least and most disparate pairs of Ss, where correlation between Ss' observed

performance was used as a measure of disparity.

Analysis of Group Data

A group-regression equation based on the combined data of 25 Ss yielded a multiple correlation of .77. An F test for significance of the multiple correlation ($df = 10/39$) demonstrated that the 59% of the averaged performance variance accounted for was a significant proportion ($p < .05$). Predicted values from the beta-weights of the regression equation, were also computed. Table 1 also shows correlations of individual Ss' observed latencies with the group observed latencies ranging from .56 to .75, and correlations of individual Ss' predicted latencies with group predicted latencies ranging from .90 to .98.

Analysis of Reliability Data

Test-retest reliability was used as an indicant of performance stability over a period of time, since interest centered on how uniform the individual remains rather than on the internal consistency of the task. Mean observed latencies for the two sets of data were used to obtain two multiple-regression equations for S 25, and the corresponding predicted latencies were then found. Beta-weight profiles resulting from the regression analyses of the replications are shown in Fig. 5. Table 1 shows a multiple correlation of .65 for the first replication and .76 for the second replication. The correlation between the two sets of observed latencies was .84 ($p < .001$), which was higher than any correlation between two Ss, while the predicted latencies correlated .97, which was no better than many of those between Ss.

Correlations with Form Measures

The 80 form measures were correlated with mean observed latencies for each S and for the group. Correlations of the group and the two replications of S 25 with selected measures are shown in Table 2. All correlations increased for the replication of S 25, indicating differentiation learning, while the group

Fig. 5. Beta-weight profiles for two replications of a single S.

correlations were usually higher than for individual Ss, probably due to increased reliability of the mean latencies. In general, the measures that correlated highest with latency to recognize vary with dispersion of form contour, either along an axis (elongation) or in any direction (jaggedness). Intercorrelations of the measures are shown in Table 3.

Analysis by Sessions

The data were also summarized by taking means across Ss within each session of 50 trials so that regression equations were computed for sessions separately. Comparison of the beta-weight profiles for the 1st through the 25th sessions showed no significant changes in cue-utilization strategies as Ss progressed from the 1st to the 25th trial.

DISCUSSION

Several important conclusions can be drawn relevant to individual differences and application of a multivariate psychophysics to form recognition. It was apparent from comparisons made that Ss differed somewhat in the extent to which they used a cue but very little in whether they used a cue or not. The results of this experiment encourage construction of a

Table 2
Correlations of Selected Measures (M) with Group Performance and with the Performance of an Individual Subject and His Replication

	Measure	Group	S25	S25R
M18	Variance of the y coordinates	-.62	-.51	-.58
M23	Perimeter	-.64	-.52	-.62
M27	Second moment of deviation from a perfect polygon	-.70	-.52	-.63
M28	Second moment of side length	-.52	-.33	-.43
M41	Second moment of distant radials	-.61	-.40	-.55
M74	Second perimeter moment of y at zero deg rotation	-.65	-.52	-.59
M77	Maximum second perimeter moment	-.66	-.48	-.59
M78	Maximum absolute third perimeter moment	-.65	-.46	-.54

Table 3
Intercorrelations of Selected Measures

	M18	M23	M27	M28	M41	M74	M77	M78
M18								
M23	.53							
M27	.61	.89						
M28	.48	.50	.80					
M41	.69	.68	.72	.58				
M74	.90	.64	.67	.41	.70			
M77	.78	.67	.81	.74	.78	.83		
M78	.75	.73	.84	.66	.73	.81	.89	

single multiple-regression equation for a group of Ss with little error in application of the equation to various Ss making up the group.

Two further extrapolations should be justifiable from these data: The equation predicting recognition latencies from factor scores is generalizable to both the population of individuals from which Ss were sampled and to the population of forms from which the stimuli were sampled. A third generalization, that the equation applicable to an individual S's data is a good predictor of his further performance in the task, also appears warranted. Note, however, that this prediction is no better for the second testing of that S than it is for two Ss with highly similar strategies. For S 25, the correlation between the latencies predicted from the first replication and the observed latencies of the second replication was .63, while the correlation between predicted latencies of one S and observed latencies of another S, for two Ss who correlated .84 on observed latencies, was .62.

Individual Ss

The results were best exemplified by the similarities among profiles of beta-weights for the 25 Ss, illustrating that if a cue was useful for one S, it was useful for all Ss. The figures also show that Ss differ somewhat in the extent to which they used a cue, as indicated by the range of beta-weights within any given factor. The fact that correlations among Ss increased in every case when predicted latencies were used instead of observed latencies further indicates that the cues used by Ss were probably very nearly the same. This was also shown by the similarity of beta-weight profiles for the two Ss who correlated .49 on observed latencies but .97 on predicted latencies. The factor analyses of both the observed and the predicted latencies show that Ss are typically responding in the same fashion and using essentially the same cue-utilization strategy.

Group Data

In general, the group beta-weight profile did not differ qualitatively from the profiles of individual Ss. Correlations of individual S's observed latencies with group

observed data and correlations between latencies predicted from individuals and from group data suggest that a group-regression equation was a good representative of any given S's equation. The extent to which the group equation could be used to predict individual observed latencies was revealed by the correlations between the group predicted data and the individual observed data, which ranged between .56 and .75.

Reliability Data

The reliability coefficient for the observed data of S 25 and the correlation between the predicted latencies for the two sets of data indicate stability in his cue-utilization strategy from test to retest. Of the variance in his performance, 69% was considered reliable, while 50% was accounted for by the regression equation. The 19% difference was either error variance or due to use of information not measured.

Knowing that people differ radically in their responses to stimuli should lead one to hypothesize greater individual differences than were found here. However, physiological experiments with visually naive kittens (Hubel & Wiesel, 1963) and studies of eye-fixation patterns of human newborns (Salapatek & Kessen, 1966) have suggested that the infant comes equipped with visual pathways capable of abstracting pattern features. If the visual pathways are laid down by genetic template, then perceptual registration of patterns is probably highly similar from one individual to the next. While differential experience with patterns is likely to lead to different cue-utilization strategies, equal exposure to abstract, unfamiliar forms may have allowed exhibition of common cue usage.

Although the extent to which these results generalize to tasks other than the recognition task has not been determined, the similarity of discrimination, detection, identification, and speed of learning to recognition leads one to postulate similar results for those tasks. Highly similar cues in these very basic tasks would encourage the use of multivariate psychophysics to determine changes in cue-utilization strategy as a function of predifferentiation,

perceptual learning, attached meaning, etc. The results suggest that once cues of sufficiently high order have been specified, the method could be applied fruitfully to more complex perceptual problems.

In conclusion, it should be noted that the demonstrated efficacy of a multivariate psychophysics has important implications for theory of pattern recognition. Such data were lacking in extensive treatment of the topic by Neisser (1967) and yet provide convincing evidence for feature analysis. The factors used to account for performance variability were correlated with form measures that may well be related to the elements of feature analysis. Correlates of Ss' recognition performance were represented physically, for example, by measures that can be described as elongation and jaggedness. The obvious analogue between form attributes weighted by Ss in recognition and feature analyzers that perform the weighting should not be overlooked in further theorizing.

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NOTES

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