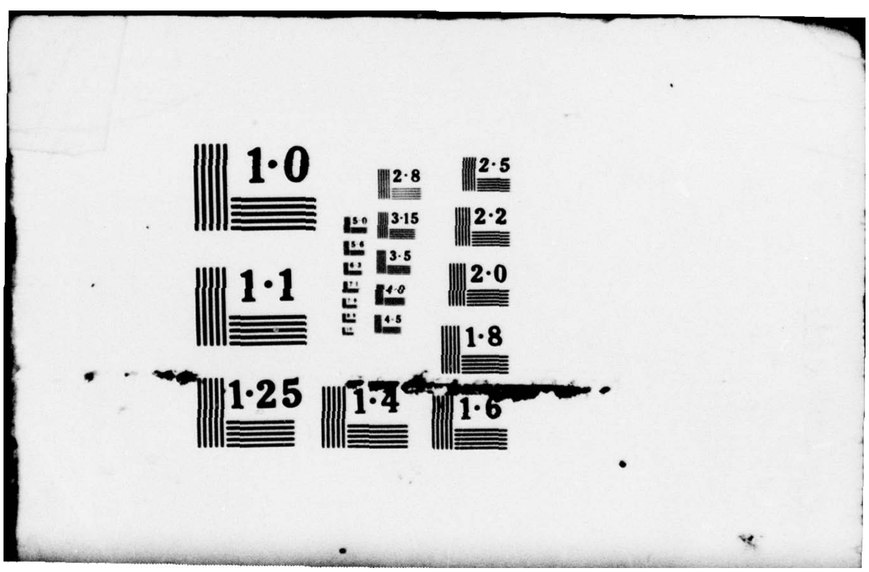
AD-A071 806 BOLT BERANEK AND NEWMAN INC CAMBRIDGE MA F/G 12/1
THE OBSERVER'S USE OF PERCEPTUAL DIMENSIONS IN SIGNAL IDENTIFIC--ETC(U)
JUN 79 D J GETTY, J B SWETS, J A SWETS N00014-76-C-0893
UNCLASSIFIED BBN-3930 NL

1 OF 1
AD
A071806

END
DATE
FILMED
8-79
DDC


1·0
2·8
2·5
3·15
2·2
3·5
2·0
4·0
4·5
1·1
1·8
1·25
1·4
1·6

Bolt Beranek and Newman Inc.

Report No. 3930

The Observer's Use of Perceptual Dimensions in Signal Identification

David J. Getty, Joel B. Swets, and John A. Swets

June 1979

Prepared for:
Engineering Psychology Programs, Office of Naval Research
ONR Contract No. N0014-76-C-0893
Work Unit No. NR 196-145

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER 3930	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) (6) The Observer's Use of Perceptual Dimensions in Signal Identification		5. TYPE OF REPORT & PERIOD COVERED (9) TECHNICAL REPORT.
		6. PERFORMING ORG. REPORT NUMBER (15)
7. AUTHOR(s) (10) David J. Getty, Joel B. Swets, John A. Swets		8. CONTRACT OR GRANT NUMBER(s) N00014-76-C-0893
9. PERFORMING ORGANIZATION NAME AND ADDRESS Bolt Beranek and Newman Inc. 50 Moulton Street Cambridge, Massachusetts 02138		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 196-145
11. CONTROLLING OFFICE NAME AND ADDRESS Engineering Psychology Programs Code 455, Office of Naval Research		12. REPORT DATE (11) June [illegible]79
		13. NUMBER OF PAGES 47
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office) (12) 47p		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

(14) BBN-3930

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

Approved for public release; distribution unlimited

18. SUPPLEMENTARY NOTES

To be published in Attention and Performance VIII, R. S. Nickerson (ed.). Hillsdale, N. J.: Laurence Erlbarm Assocs., in press.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

signal detection, signal identification, human observers, complex visual stimuli, multidimensional scaling, decision processes in perception, pattern recognition, tuning processes in perception

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

We examine a model of the process of stimulus identification, which assumes that complex visual or auditory stimuli are represented as vectors in a multidimensional perceptual space, and which postulates a simple probabilistic decision process based on the geometric structure of the perceptual space. We present evidence from several conditions of an identification task that human observers engage in a continuing, dynamic process in which

over

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

060 100

dimension salience weights are tuned to optimize identification performance. In addition, we verify the reliability of the INDSCAL multidimensional scaling procedure in deriving the geometric structure of the observers' perceptual space for the set of visual spectrograms used in our identification tasks. We also present evidence supporting an assumption of dimensional decomposability made in the decision process. Finally, we observe that the model is successful in accounting for approximately 90 percent of the variance in individual confusion matrices, averaged over 18 observers x conditions.

Table of Contents

Figure Captions

Table Captions

Introduction

The process of identifying a complex visual or auditory stimulus from a set of similar stimuli requires both a psychological representation for each candidate stimulus and an appropriate decision process to govern the choice among them. In recent work (Getty, Swets, Swets, and Green, in press), we describe an approach to understanding complex stimulus identification that involves two parts: (1) the derivation of a multidimensional perceptual space for a set of complex stimuli from the application of a multidimensional scaling (MDS) procedure to judgments of stimulus similarity, and (2) the use of a probabilistic decision model to predict the identification confusion matrix based on the geometric structure of the MDS-derived perceptual space. Using this approach with a set of eight visual spectrograms of real underwater sounds, we were quite successful in predicting the confusion matrices for individual observers, accounting for an over-all average of 94 percent of the observed variance across several conditions of both complete- and partial-identification tasks. In another study that proposed a related type of probabilistic decision model -- and again using a MDS procedure to determine the perceptual space -- Howard, Ballas, and Burgy (1978) were able to account for between 61 and 96 percent of the variance in individual confusion matrices obtained for a set of 16 complex acoustic patterns.

In our previous study, we found that observers appeared to weight differentially information derived from the several perceptual dimensions in such a way as to maximize the average probability of a correct identification. Similarly, Howard et al. reported that their model estimates of dimension "emphasis" supported the hypothesis that relative emphasis was allocated to dimensions by listeners so as to maximize the average probability correct.

In this paper, we pursue the implication of the findings that observers are flexible in their use of perceptual dimensions. Specifically, we suggest that observers are engaged in a continuing, dynamic process of adaptive tuning of dimension weights so as to optimize a particular, task-dependent criterion of performance. In the usual identification task, this criterion is either explicitly stated, or implicitly understood, to be maximizing the probability of a correct identification. Clearly, however, changes in the task could invoke other criteria, such as maximizing the probability of correctly identifying some subset of the stimuli, or maximizing the probability of correctly classifying the stimuli into a particular set of categories. Different criteria would dictate different optimal patterns of relative dimension weights.

The optimal pattern of dimension weights is obviously stimulus-dependent as well as task-dependent. For example, given the optimal pattern of relative dimension weights for a particular set of stimuli, if we now decrease the range of stimulus variation on one of the perceptual dimensions towards zero, we may expect the optimal weight on that dimension, relative to the others, to likewise decrease towards zero. In the identification experiment that follows, we made use of this manipulation in several different conditions to produce different expected patterns of dimension weights. Our objectives in these conditions were to determine whether or not tuning of dimension weights occurs and, if so, whether or not the optimization criterion seems to be maximization of the probability of correct identification.

We had several other objectives in this experiment as well. First, we wished to test the reliability of the perceptual space derived from INDSCAL (Carroll and Chang, 1970; Carroll, 1972; Carroll and Wish, 1974), which is the MDS procedure we applied to judgments of stimulus similarity. Second, we wished to test a decomposability assumption of the decision model. Finally, we wished to obtain multiple tests of the model's adequacy in predicting individual confusion matrices under a variety of conditions, using a set of stimuli that were sufficiently similar to yield a high rate of confusion errors. Each of these goals is elaborated at appropriate points in the discussion.

The Identification Model

We describe here, briefly, the decision model which predicts the distribution of response probabilities for each stimulus, given the relative loci of the stimuli in the observer's multidimensional perceptual space. (For a fuller discussion of the model, see Getty et al., in press).

We assume that the distance between stimulus S_i and stimulus S_j in the perceptual space is given by a weighted Euclidean metric:

$$D_{i,j} = \left[\sum_k w_k (\psi_{i,k} - \psi_{j,k})^2\right]^{\frac{1}{2}} \qquad (1)$$

where w_k is a salience weight measuring the relative importance of dimension k ($w_k \geq 0$ and $\Sigma w_k = 1$), and $\psi_{i,k}$ is the coordinate value of stimulus S_i on dimension k. The salience weights are model parameters; the stimulus coordinates are obtained from the MDS procedure applied to judgments of stimulus similarity.

We define a set of confusion weights $C_{i,j}$ such that the confusability of stimulus S_i with stimulus S_j is given by

$$C_{i,j} = \exp(-\underline{a}\, D_{i,j}) \tag{2}$$

where $\underline{a}$ is an observer sensitivity parameter, greater than zero, and therefore $C_{i,j}$ is bounded between 0 and 1. This exponential relationship has received support both in our earlier experiments and in Shepard's related work on stimulus generalization (1957, 1958a, 1958b).

Finally, the conditional probability of giving the response assigned to stimulus S_j, R_j, when stimulus S_i was presented is given by Luce's biased choice model (1963):

$$Pr(R_j|S_i) = \frac{b_j\, C_{i,j}}{\sum_k b_k C_{i,k}} \tag{3}$$

where b_j is a response bias weight describing the relative bias towards making response R_j, ($b_j \geq 0$ and $\Sigma b_j = 1$) and k is an index over the set of stimuli.

Method

Apparatus

All experimental events were controlled by a DEC PDP-11/34 minicomputer. The visual stimuli were constructed on a COMTAL 8000-SA image-processing system and displayed within a 512 x 512 pixel (picture element) matrix which filled a 24-cm square area on a CONRAC 17-inch (43-cm) SNA television monitor. The monitor brightness and contrast were adjusted such that middle gray (128 gray units on the COMTAL scale) had a luminance of about 46 cd/m^2, and full white (255 gray units) a luminance of about 480 cd/m^2. Ambient room lighting was maintained at a dim level.

In both the similarity-judgment and identification tasks, three observers (one group) sat at one time at individual video terminals (Lear Siegler ADM-3A) approximately 2 m from the stimulus-display monitor, whose center was about 1.1 m above the floor.

Stimuli

Our stimuli were synthesized visual spectrograms of complex, two-formant sounds. The stimuli were displayed as frequency (horizontal axis) versus time (vertical axis) versus energy (darkness -- the greater the energy, the darker the trace). They varied along three physical dimensions: (1) location of the center of the first formant, (2) location of the center of the second formant, and (3) the frequency of sinusoidal amplitude-modulation (AM) in the temporal direction (corresponding to a low-frequency periodicity in the sound).

A basic set of 27 stimuli was defined by all combinations of three equally-spaced values on each of the three dimensions. The values for the location of the first formant were 20, 25, and 30 elements from the left edge of the stimulus image. (The stimulus was 126 elements wide by 128 elements high.) The three values for the location of the second formant were 90, 95, and 100 elements from the left edge. The three frequencies of amplitude modulation were 15, 17, and 19 cycles per stimulus. The 27 stimuli were "randomly" partitioned into three sets of nine stimuli, subject to the following constraints: (1) no two stimuli within a set shared more than one coordinate value in common; (2) for each set, each of the three values on each of the three dimensions occurred with exactly three of the stimuli. The purpose of these constraints was to obtain a uniform distribution of stimuli throughout the space within each set. The resulting three sets, labelled A, B, and C, are given in Table 1.

The stimulus image was constructed by subtracting profiles of the two formants from a background of random, Gaussian-distributed noise. The noise consisted of a 126 x 128 (w x h) matrix of elements, each element having an independent gray value sampled anew on each trial from a Gaussian distribution with a mean of 128 gray units and a standard deviation of 25 gray units. The first and second

Table 1

Physical values defining each stimulus on the three primary dimensions (AM, F1, F2) and the two derived dimensions (Width, Location)

Stimulus Number	AM	F1	F2	Width[a]	Location[b]
Stimulus Set A					
1	17	30	100	70	65.0
2	17	25	90	65	57.5
3	19	25	100	75	62.5
4	15	25	95	70	60.0
5	15	20	100	80	60.0
6	17	20	95	75	57.5
7	19	20	90	70	55.0
8	15	30	90	60	60.0
9	19	30	95	65	62.5
Stimulus Set B					
1	15	20	95	75	57.5
2	15	25	90	65	57.5
3	15	30	100	70	65.0
4	17	20	90	70	55.0
5	17	25	100	75	62.5
6	17	30	95	65	62.5
7	19	20	100	80	60.0
8	19	25	95	70	60.0
9	19	30	90	60	60.0
Stimulus Set C					
1	15	20	90	70	55.0
2	15	30	95	65	62.5
3	19	20	95	75	57.5
4	17	30	90	60	60.0
5	15	25	100	75	62.5
6	17	25	95	70	60.0
7	19	30	100	70	65.0
8	17	20	100	80	60.0
9	19	25	90	65	57.5

[a] Width = F2 - F1

[b] Location = (F1 + F2)/2

formants were given Gaussian-shaped horizontal profiles with a peak amplitude of 40 gray units and standard deviations of 10 and 18 pixels, respectively. The amplitude modulation was imposed on the resulting image in the vertical direction with a modulation depth of 50 percent. Finally, each element was expanded to fill a 2 x 2 pixel area, resulting in an image 252 x 256 pixels on the display monitor.

These high-contrast stimuli, were used in the similarity-judgment task. In order to increase confusability of the stimulus set for the identification task, and to increase their realism, the stimuli were modified in two ways. First, we introduced temporal variability or "wobble" into the displayed value of the stimulus on each of the three dimensions. Thus, scanning down each of the examples shown in Fig. 1, you will see (independent) wobble in the location of each of the two formants and in the period of the amplitude modulation. For each dimension, the temporal pattern of deviation from the value specified for the stimulus was generated by summing together four sinusoids with frequencies 1, 2, 3, and 4 cycles/stimulus, each beginning at a different random phase that was sampled anew on each trial. By summing only integral frequencies, we guaranteed that the total deviation about the specified dimension value, integrated down the length of a stimulus image, was always zero. As the second modification to increase confusability we reduced the signal-to-noise ratio considerably by decreasing the peak amplitude of the first and second formants from 40 gray units to 8 and 10, respectively. As a result, the formants were barely perceptible within the stimulus.

Observers

Two groups of three observers, referred to as Groups A and B, participated in the experiment. Four of the six observers were recruited from an observer pool and paid for their assistance; the other two were members of BBN's technical staff, including one of the experimenters (JBS).

Procedure

Similarity-Judgment Task. The observers were instructed to rate similarity of pairs of stimuli on a 7-point scale, with the scale endpoints "1" and "7" indicating very dissimilar and very similar stimuli, respectively. Each of the 36 possible pairs for a particular set of nine high-contrast, wobbleless stimuli was presented side-by-side on the display monitor for 15 seconds, followed by an observer-paced response interval. Four blocks of 36 trials were presented, using a different random order for each block, and with the left-right position of stimuli within a given pair counterbalanced over blocks.

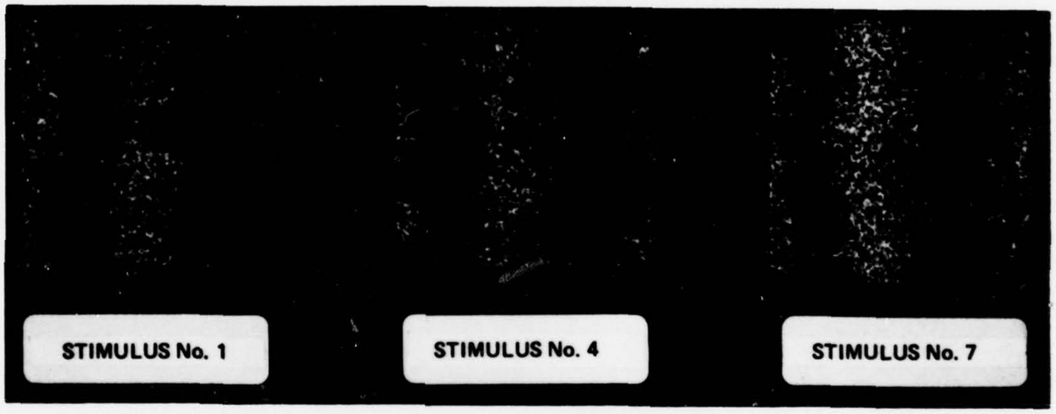


Fig. 1. Examples of high contrast stimuli with wobble present on all three physical dimensions. All three values used on each of the three dimensions are shown across the three stimuli; these values are given for Stimuli 1, 4, and 7 (Stimulus Set A) in Table 1.

All six observers participated in two different conditions of the similarity-judgment task. The two conditions were run successively, between the first and second conditions of the identification task.

Identification Task. Each trial began by blanking of the display monitor screen, followed approximately 2.5 seconds later by a low-contrast, wobbly display of a stimulus image, chosen randomly from the set of nine being used. Each observer then made a self-paced identification response (from the numbers "1" to "9" on the keyboard), making reference to a folder of labelled, high-contrast, wobbleless Polaroid photographs of the nine stimuli. After all observers had responded, the number of the presented signal was displayed on each observer's terminal. The stimulus number and stimulus image remained on display for for approximately two seconds after which the next trial began. Trials were grouped into 50-trial blocks, with three blocks presented each day for seven days for each of three conditions of the task for each group. The nature of each condition for each group is discussed later as each arises.

Derivation of the Perceptual Space

The primary purpose of the first similarity-judgment condition was to derive a multidimensional representation of the observers' perceptual space in terms of both the identity of the psychological dimensions comprising the space and the relative loci of the stimuli within the multidimensional space. Stimulus Set A (as defined in Table 1) was used in this condition -- the same set of nine stimuli used for all observers in the immediately preceding identification condition. It was hoped that by running the similarity-judgment task immediately after a condition of the identification task, and by using the same stimulus set in both cases, that the same perceptual dimensions salient to the observers in the identification task would remain salient in the similarity-judgment task. Our concern stemmed from a previous study (Getty et al., in press) in which one dimension (low-frequency periodicity or amplitude modulation) that was apparently utilized by observers when identifying the stimuli was not used when they rated similarity of the stimuli. In anticipation of our present results, that problem did not arise here.

The objectives of the second similarity-judgment condition were to provide a test of the reliability of the INDSCAL procedure, and to test the decomposability property of INDSCAL. Decomposability is the assumption that the distance between any two points in the derived multidimensional space can be decomposed into independent contributions from each of the derived dimensions (see

Tversky and Krantz, 1970). Stimulus Set B, the stimuli used in this condition and defined in Table 1, shared with Stimulus Set A the same three values on each of the three physical dimensions, although in different, unique combinations. Given that these new stimuli lay in the same region of the physical space, we would expect to derive the same perceptual dimensions from INDSCAL in the second condition as in the first condition, and to find the same psychophysical mapping of each physical dimension into its corresponding psychological dimension. This latter expectation requires, in part, that decomposability be satisfied.

Results

We calculated the average similarity rating for each of the 36 stimulus pairs, separately for each observer and each condition. The average for each pair was based on judgments from the second, third, and fourth blocks of trials; the first block of trials was regarded as practice and excluded from analysis. The average ratings for each observer were then submitted to MDS analysis, separately for the two conditions, using the metric version of INDSCAL.

Condition 1. The rating data for stimulus Set A were fitted well by a three-dimensional solution which accounted for 89 percent of the variance in the data. The first psychological dimension is clearly identified with the physical AM dimension. The psychophysical relationship, shown in the top, left panel of Fig. 2, appears to be highly linear, at least over the physical range utilized. The best-fitting straight line accounts for 99 percent of the observed variability in the psychological dimension.

Surprisingly, the identities of the other two psychological dimensions are not the locations of the first and second formants, those being the other two physical dimensions manipulated in the construction of the stimuli. Rather, they appear to be identified with a related pair of physical dimensions obtained by a 45-degree rotation of the F1 and F2 axes. This geometric relationship can be seen in Fig. 3 which shows the stimuli plotted in the ψ_2, ψ_3 plane. Stimuli sharing the same value of F1 are connected by solid lines; those sharing the same value of F2 are connected by dashed lines. A possible basis for the obtained psychological dimensions becomes apparent if one regards each stimulus as being composed of a central vertical column bounded on either side by F1 and F2 (see Fig. 1). Then the physical dimension corresponding to ψ_2 is the width of the column -- the distance between F1 and F2 -- and the physical dimension corresponding to ψ_3 is the location of the column, that is, the location of the midpoint between F1 and F2, given by (F1 + F2)/2.

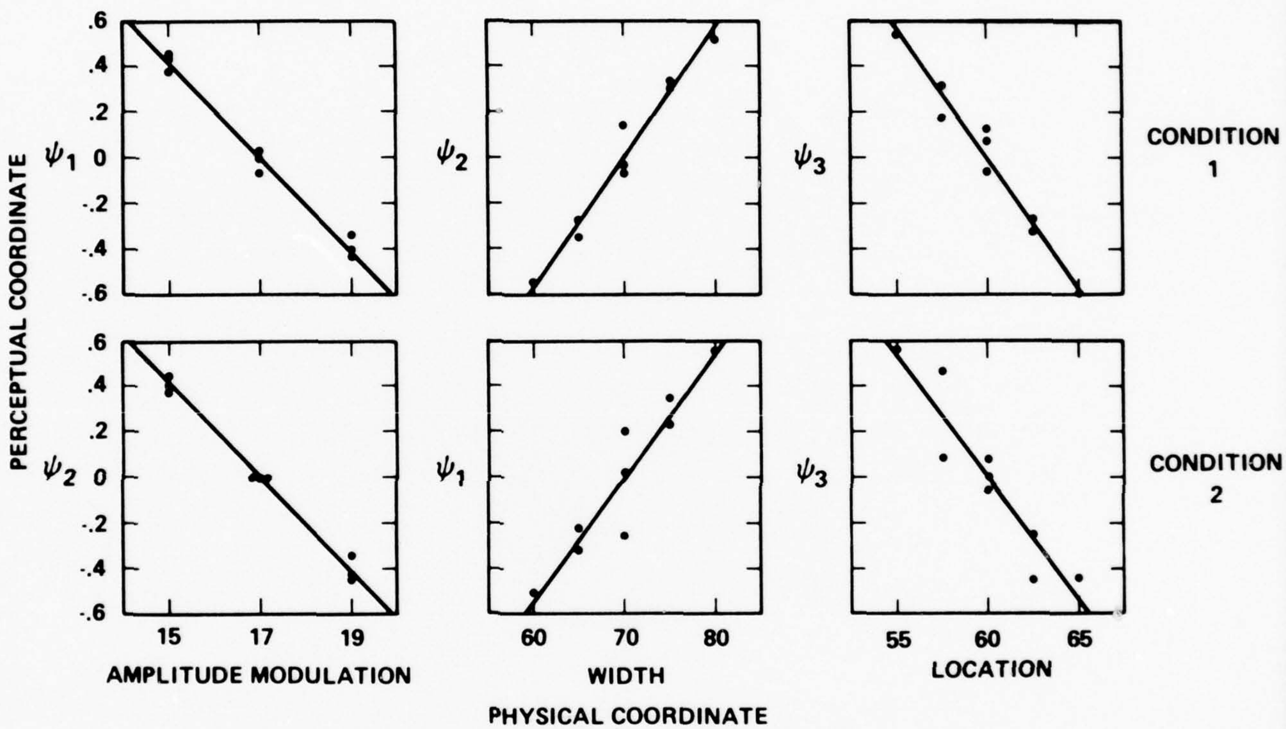


Fig. 2. The observed psychophysical relations between the three physical dimensions (AM, Width, and Location) and the corresponding INDSCAL-derived perceptual dimensions (ψ_1, ψ_2, and ψ_3), for each of the two similarity-judgment conditions. In each case, the best-fitting straight line is shown.

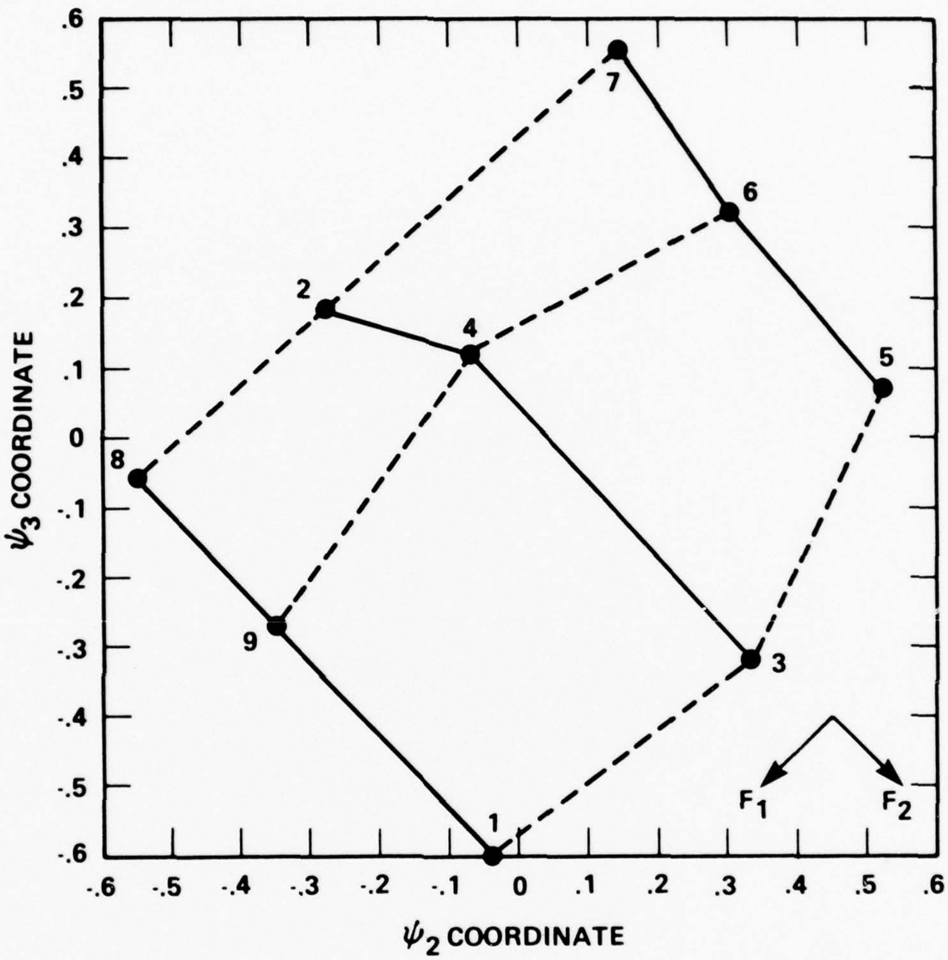


Fig. 3. The INDSCAL-derived coordinates of each of the nine stimuli in Stimulus Set A on perceptual dimension 3 plotted against coordinates of the stimuli on perceptual dimension 2. Stimuli sharing the same F1 (F2) value are connected by solid (dashed) lines.

Plotting the perceptual coordinates of the stimuli on perceptual dimensions 2 and 3 against the physical measures of Width and Location, respectively, shown in the righthand, top two panels of Fig. 2, we see that both psychophysical relations are quite linear. The best-fitting lines account for 97 and 96 percents of the variance in ψ_2 and ψ_3, respectively.

<u>Condition 2</u>. The rating data for stimulus Set B were fitted well by a three-dimensional INDSCAL solution which accounted for 86 percent of the variance in the data, nearly the same value obtained in Condition 1.

Correlating the three perceptual dimensions with the physical dimensions determined in Condition 1, we found a correspondence between ψ_1 and Width, between ψ_2 and AM, and between ψ_3 and Location. As in Condition 1, the psychophysical relations, shown in the lower row of Fig. 2, are all quite linear. The best-fitting straight lines account for 89, 99, and 87 percents of the variance on the ψ_1, ψ_2, and ψ_3 dimensions respectively.

We are thus able to account for the similarity rating of two independent sets of stimuli drawn from a common physical space in terms of the same three perceptual dimensions, although the ordering of AM and Width dimensions is reversed in the INDSCAL solution of the second condition.

Moreover, both sets of data support the conclusion that the perceptual dimensions are linearly related to their respective physical dimensions.

Salience Weights. In addition to the coordinates for each stimulus in the multidimensional space, INDSCAL also produces a vector of salience weights for each observer reflecting the relative importance of each dimension for that observer. The derived salience weights for each observer in both conditions of the task are shown in Fig. 4. The results indicate that there are substantial individual differences in the pattern of salience weights across observers, but that there is considerable stability in the pattern of weights for a given individual across the two conditions.

Prediction of Identification Confusion Matrices

The first condition of the identification task was the same for both groups of observers, and made use of the nine patterns comprising Stimulus Set A. It provided a first test of the model's accuracy in predicting confusion matrices and served as a reference for the other conditions.

Prior to starting this condition, all observers received six sessions of practice (150 trials/session) identifying high-contrast, wobbleless stimuli, and one day

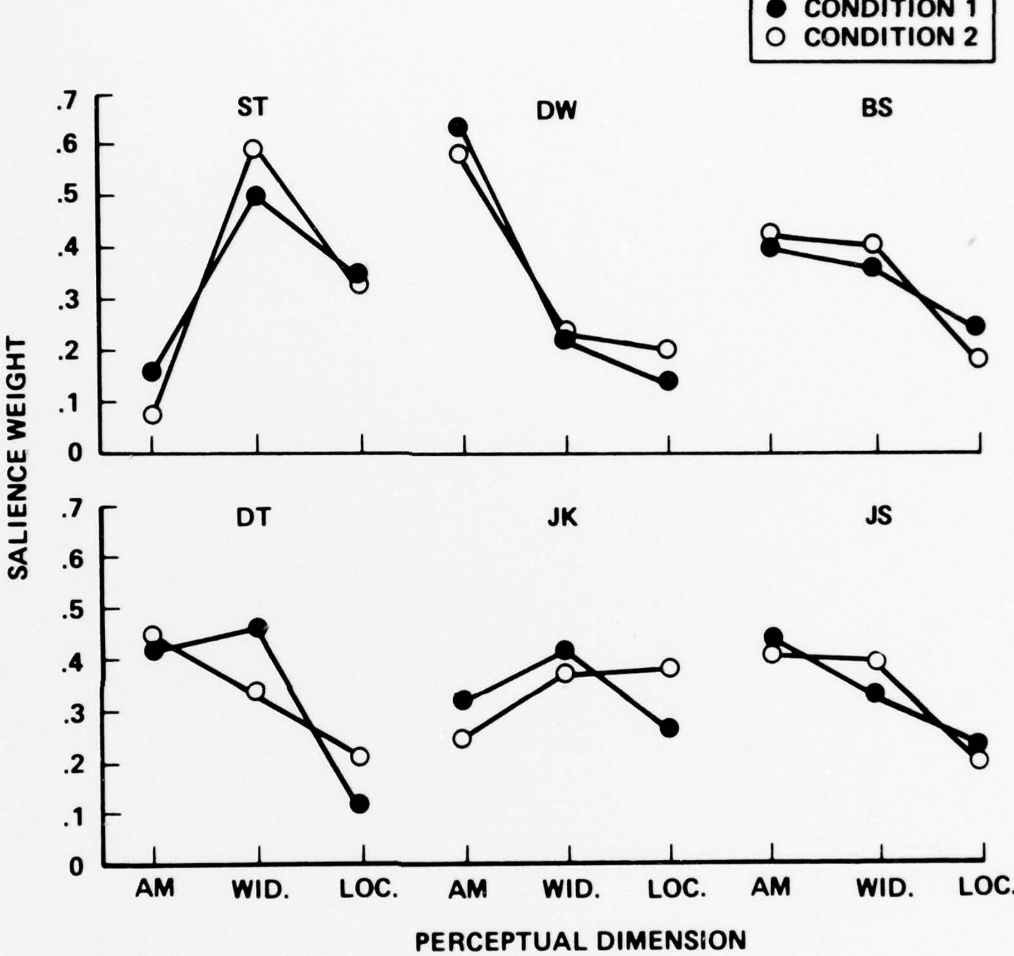


Fig. 4. Relative dimension salience weights from INDSCAL for each of the three perceptual dimensions derived from INDSCAL in the two conditions of the similarity-judgment task, for each of the six observers.

of practice identifying low-contrast, wobbly stimuli. Identification data were then collected for seven days; the resulting confusion matrix for each observer contained 1050 trials.

Model Analysis

Parameter Estimation. Model parameters were estimated separately for each observer in a two-stage process. First, an iterative parameter-estimation procedure was used to determine the set of response bias weights, b_j, that minimized the summed squared deviation between obtained and predicted confusion matrices (as given by Eq. 3). The response bias weights were then fixed at their estimated values and a second estimation procedure carried out using the full structure of the model (Eqs. 1, 2, and 3) and the normalized three-dimensional loci of the stimuli obtained from the INDSCAL analysis of the similarity-judgment task. Estimates were obtained for the three salience weights, w_1, w_2, and w_3, and the sensitivity parameter, $\underline{a}$.*

Prediction of Individual Confusion Matrices. The model predicts the individual confusion matrices very well,

*We estimated the dimension salience weights instead of using the INDSCAL-derived weights for each observer because the requirements of the identification task may well result in salience weights different than those of the similarity-judgment task.

accounting for an average of 92 percent of the variance across the six observers. Moreover, we did not find any obvious violations of model assumptions in the remaining variance not accounted for. The goodness-of-fit and the estimated model parameter values are shown in Table 2 (Condition 1) for each observer. The relative importance of the three dimensions appears to vary to some extent across observers; however, there is a general tendency for Width and Location to be weighted about equally, and both to be weighted more heavily than AM.

The predicted and obtained response distributions for each stimulus are shown in Fig. 5 for three of the six observers, chosen to represent the worst (DT), median (ST), and best (DW) fits of the model to the data. The over-all probability of a correct identification was 0.50, averaged over stimuli and observers. Thus, about half of the approximately 100 responses contributing to each distribution were confusion errors. In Fig. 5, it can be seen that the model generally predicts with considerable accuracy both the probability of a correct identification -- the highest peak in most distributions -- and the patterns of confusion errors. Even in cases where the prediction of the exact magnitude of a major confusion response is not accurate -- for example, Response 3 to Stimulus 1 for observer ST -- the model has at

Table 2

Proportion of variance accounted for by the model and estimated parameter values for each observer

OB	r^2	w_1 (Amp. Mod.)	w_2 (Width)	w_3 (Loc.)	$\underline{a}$
CONDITION 1					
GROUP A					
BS	.95	.07	.46	.47	5.9
ST	.91	.00	.45	.55	4.5
DW	.98	.43	.34	.24	6.1
AVG	.95	.17	.42	.42	5.5
GROUP B					
JK	.86	.23	.38	.38	4.3
JS	.97	.22	.45	.34	5.4
DT	.83	.12	.47	.41	3.6
AVG	.90	.19	.43	.38	4.4
COND. AVG.	.92	.18	.43	.40	5.0
CONDITION 2					
GROUP A					
BS	.96	.09	.31	.61	5.8
ST	.92	.00	.44	.56	5.1
DW	.99	.36	.34	.31	7.3
AVG	.96	.15	.36	.49	6.1
GROUP B					
JK	.81	.43	.08	.48	3.3
JS	.83	.33	.11	.56	4.2
DT	.64	.10	.52	.38	3.1
AVG	.76	.29	.24	.47	3.5
CONDITION 3					
GROUP A					
BS	.97	.00	.50	.50	6.0
ST	.94	.00	.49	.51	4.8
DW	.96	.50	.34	.16	6.8
AVG	.95	.17	.44	.39	5.9
GROUP B					
JK	.89	.17	.42	.42	4.2
JS	.96	.20	.38	.42	5.6
DT	.91	.34	.33	.34	4.0
AVG	.92	.24	.38	.39	4.6

least successfully predicted the response to be a major confuser.

One can also see in Fig. 5 that while the patterns of confusion errors for a particular stimulus are often similar across observers, there are some differences -- occasionally large. The model accounts for these individual differences based on a different pattern of dimension salience weights for each observer.

A Test of Dimensional Decomposability

The decision model assumes that the measure of interstimulus distance is decomposable into independent contributions from each of the perceptual dimensions (Eq. 1). In the first condition of the identification task just described, the stimuli were the same as those used in the similarity-judgment task from which the perceptual representation of the stimuli was derived. Our objective in a second condition of the identification task was to test the decomposability assumption using the perceptual space derived from one set of nine stimuli (Stimulus Set A in Table 1) to predict the confusions for an independent set of nine stimuli (Stimulus Set C). These new stimuli share with the old set the same three values on each of the three dimensions, but in new, independent combinations. If each

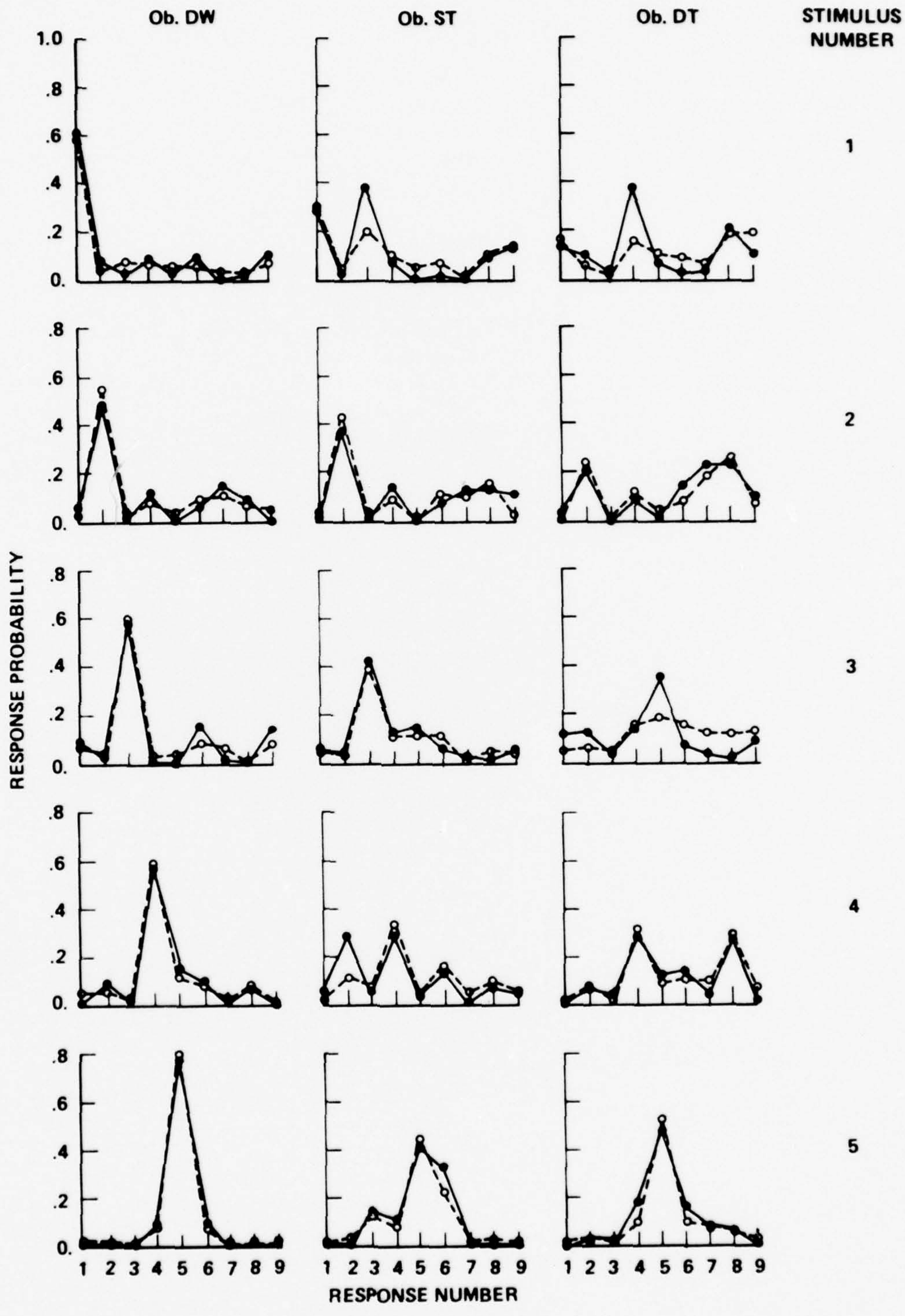


Fig. 5. Distribution of response probability for each of the nine stimuli in Condition 1, for three of the six observers. Obtained distributions are given by filled circles; predicted distributions are given by open circles.

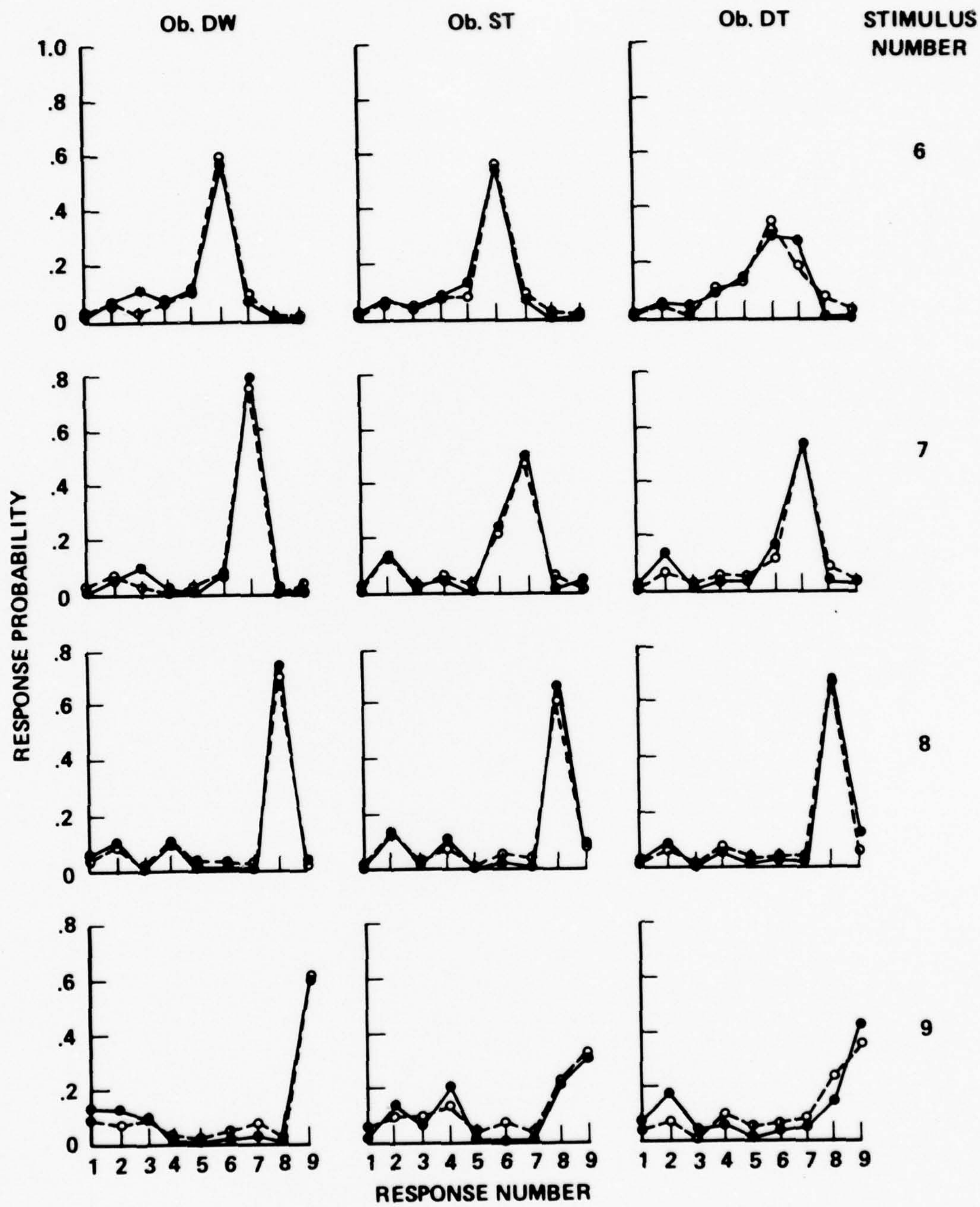


Fig. 5. Continuation.

dimension contributes independently to interstimulus distance, then we should do as well at predicting the confusion matrix for Stimulus Set C as for Stimulus Set A, when both predictions are based on the perceptual space derived from Stimulus Set A. If, on the other hand, decomposability is not satisfied, then we would predict response confusions less well in this condition than in the last.

The three observers of Group A were run in this condition for seven sessions. The data from the first session were regarded as practice and excluded from analysis; the 900 trials from the other six sessions were combined for each observer into a confusion matrix. The model was then fitted to each observer's data using the two-stage procedure described previously.

The results are shown in Table 2 under Condition 2, Group A. The model accounted for an average of 96 percent of the variance in the observed confusion matrices, a figure almost identical to the 95 percent of the variance accounted for in the first condition for these same observers. Moreover, the percentages of variance accounted for in the two conditions agree within one percent for each of the three observers individually. This result offers strong support for the model's assumption of dimensional decomposability.

Adaptive Tuning of Dimension Salience Weights

In this section, we investigate the flexibility shown by observers in adjusting or "tuning" the distribution of salience weights in response to changes in the set of stimuli to be identified. In particular, we hypothesize that for a given set of stimuli, the observer engages in an adaptive process of adjusting the relative salience weights over the set of perceptual dimensions so as to maximize the probability of a correct identification. In terms of the model, the optimal distribution of salience weights will clearly vary as a function of the relative average interstimulus spacing of the stimuli on each of the dimensions. With the loci on all other dimensions fixed, the optimal relative salience of a particular dimension will decrease towards zero as the average interstimulus spacing on that dimension decreases towards zero.

In each of three conditions, we made one of three physical dimensions -- Width, F1 location, and AM -- less useful to the observer by "squeezing" the values on the dimension closer together than they were in the reference condition (Condition 1). Our expectation -- and model prediction -- is that, in each case, the salience of the compressed dimension will decrease relative to its value in the reference condition* We discuss here the results only for the condition in which we compressed the Width dimension (Group B, Condition 2). The results for the other two conditions, in which we compressed F1 location (Group B, Condition 3) and AM values (Group A, Condition 3), showed effects similar in type, but less pronounced in magnitude due to the fact that we compressed the F1 location and AM dimensions less than we compressed Width. The fits of the model and parameter estimates for those other two conditions are included, however, in Table 2.

The stimuli in the compressed Width condition were identical to those in Stimulus Set A, except that the five values of Width represented among the nine stimuli were compressed from 60, 65, 70, 75, and 80 elements to 68, 69, 70, 71, and 72 elements, respectively -- a five-fold reduction in the range on this dimension.

A confusion matrix was obtained for each of the three observers in Group B, based on 900 trials from the last six

---

*Another plausible intuition suggests that as the discriminability on a dimension is decreased by compression, the observer should compensate by devoting more attention to that dimension. The model does not support this prediction because the total amount of attention to be distributed over dimensions is fixed (at unity in the model). Thus, an increase in the salience of a dimension of reduced utility is achieved only at the expense of a decrease in the salience of some other dimension of relatively enhanced utility.

of seven sessions; the first session was excluded as practice. Compressing Width had a marked effect on the over-all probability of a correct identification, reducing it from .45 for this group in Condition 1 to .29 in this condition.

In order to fit the model to the observed confusion matrices, estimates were required of the perceptual locations corresponding to the new physical Width values. These were obtained from the linear psychophysical function relating the physical and perceptual Width dimensions derived from the similarity-judgment task (see Fig. 2). The resulting goodness-of-fit values and parameter estimates are given in Table 2 (Condition 2, Group B) for each observer. For two of the observers (JK and JS), the salience weight for Width dropped markedly, as expected, from .38 and .45 in Condition 1 to .08 and .11 in Condtion 2, respectively. For the third observer (DT), however, the Width salience weight increased slightly from .47 to .52, contrary to our expectation based on adaptive tuning.

A further analysis aids our understanding of these results considerably. In order to determine the temporal course of tuning, we reanalyzed the Group B data of both Conditions 1 and 2 in successive 300-trial blocks (thirds of a condition) and fitted the model separately to each of these successive blocks. The estimated salience weights for the final 300-trial block of Condition 1 and each successive block of Condition 2 are shown for each observer by the solid lines in the left-hand panels of Fig. 6. In addition, for a particular set of stimuli -- and given the obtained estimates of an observer's response biases and sensitivity -- it is possible to determine from the model the pattern of salience weights that would maximize the observer's probability of a correct identification. We determined these optimal weights, shown in Fig. 6 by the dashed lines, for each successive block, for each observer.

Comparing observed and optimal salience weight patterns we see that observers JK and JS demonstrate relatively optimal weight patterns in the final blocks both of Conditions 1 and 2. The optimal weight pattern for Condition 2 is quite different than that for Condition 1. Both observers JK and JS redistribute their salience weights to match the new optimal patterns by the second block of 300-trials. The tuning process is sufficiently gradual, however, so that the observed pattern for both observers for the first 300 trial block of Condition 2 is intermediate between that present at the end of Condition 1 and that arrived at by the middle of Condition 2.

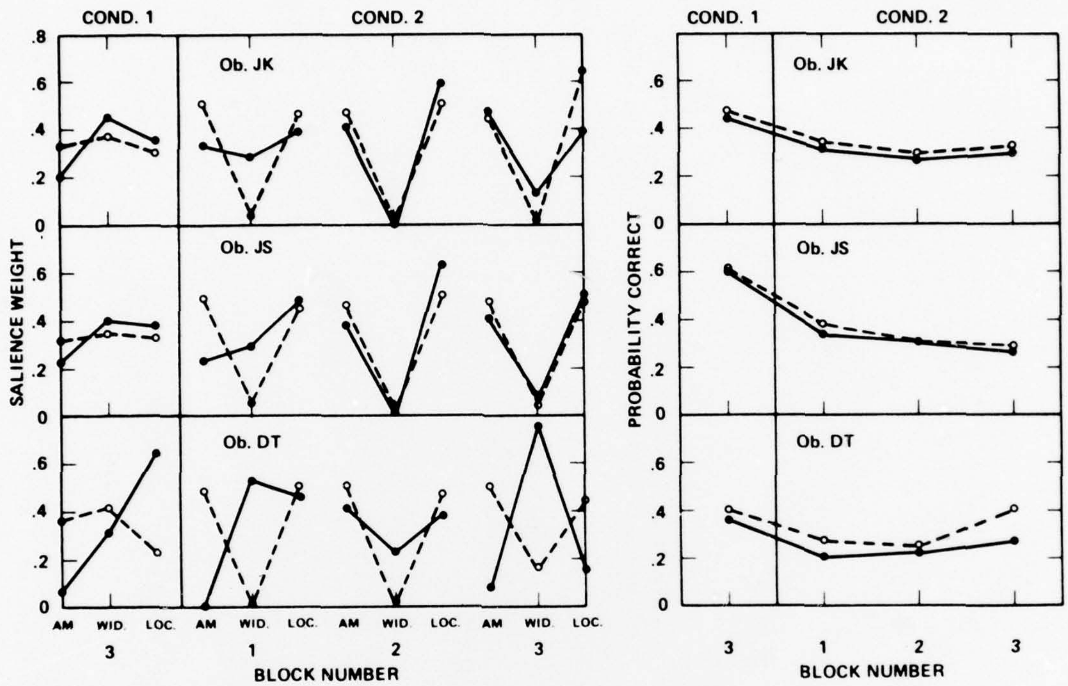


Fig. 6. Left panels: The observed (filled circles) and predicted (open circles) relative salience weights for each of the three perceptual dimensions for the final 300-trial block of Condition 1 and successive blocks of Condition 2, for each observer in Group B.

Right panels: The observed (filled circles) and predicted (open circles) probability of a correct identification for successive blocks of trials in Conditions 1 and 2 for each observer in Group B.

In contrast, a comparison of the obtained and optimal salience weight patterns for observer DT shows little evidence of tuning. Over successive thirds, the observed weight pattern changes considerably, but in ways which appear to bear little relationship to the optimal weight pattern. A possible explanation of this result becomes clear when we compare the probability of a correct identification, Pr(C), obtained when the optimal weight pattern is used with that obtained when the observed, non-optimal weight pattern is used. These optimal and observed correct identification probabilities are shown for each successive 300-trial block in the right-hand panels of Fig. 6. Not surprisingly, the observed Pr(C) is no more than a few percent below the optimal value in all cases for observers JK and JS, both of whom adopted nearly optimal weight patterns. What is surprising, however, is that the observed Pr(C) for observer DT is, on the average, no more than 6 percent below the optimal value. For our stimuli, the optimization surface determined by the three salience weights is very flat, so that relatively large departures in the weights from the optimal pattern result in only a modest decrement in identification accuracy. According to this reasoning, we may interpret the performance of observers JK and JS as indicating a high sensitivity to small deviations from optimal Pr(C) while the performance of observer DT indicates a lesser sensitivity. We speculate that if stimuli were chosen in such a way that the optimization surface were steep, we would find evidence of tuning in the performance of all observers, including that of observer DT.

Conclusions

Our results demonstrate the existence of an adaptive process of tuning of dimension salience weights in the identification process. For the identification task, the data are consistent with the hypothesis that observers tune to maximize the average probability of correct identification. Starting from a very non-optimal weight distribution, we observed that the tuning process may take place over tens or hundreds of trials. These results support the view that the human observer is indeed flexible in his or her use of perceptual dimensions in pattern identification or classification, adjusting the weighting of dimensions to the characteristics of the set of stimuli at hand and the particular requirements of the identification or classification task.

The results of the two conditions of the similarity-judgment task affirm the reliability of the INDSCAL MDS procedure in that we derived the same three perceptual dimensions, and linear psychophysical functions on all three dimensions, in both conditions.

We also obtained support for the model's assumption of dimension decomposability. Having obtained estimates of the perceptual loci for one particular set of stimuli, we were then able to predict the confusion matrix equally well for several different combinations of the same set of values on the three dimensions.

Finally, we note the over-all success of the model in predicting the confusion matrices over the three conditions of the identification task for each of the two groups of observers. Averaged over the 18 comparisons of predicted and observed confusion matrices (Table 2), the model accounted for 91 percent of the observed variance.

References

Carroll, J. D. Individual differences and multidimensional scaling. In R. N. Shepard, A. K. Romney, and S. Nerlove (Eds.). Multidimensional Scaling: Theory and Applications in the Behavioral Sciences. New York: Seminar Press, 1972, 105-155.

Carroll, J. D., and Chang, J. J. Analysis of individual differences in multidimensional scaling via an N-way generalization of "Eckart-Young" decomposition. Psychometrika, 1970, 35, 288-319.

Carroll, J. D., and Wish, M. Models and methods for three-way multidimensional scaling. In D. H. Krantz, R. C. Atkinson, R. D. Luce, and P. Suppes (Eds.), Contemporary Developments in Mathematical Psychology, Vol. II. San Francisco: Freeman, 1974.

Getty, D. J., Swets, J. A., Swets, J. B., and Green, D. M. On the prediction of confusion matrices from similarity judgments. Perception & Psychophysics, in press.

Howard, J. H. Jr., Ballas, J. A., and Burgy, D. C. Feature extraction and decision processes in the classification of amplitude modulated noise patterns. (Technical Report ONR-78-4) Washington, D. C: The Catholic University of America, July, 1978.

Luce, R. D. Detection and recognition. In Handbook of Mathematical Psychology. (Eds.) R. D. Luce, R. R. Bush, and E. Galanter. New York: Wiley, 1963, 103-189.

Shepard, R. N. Stimulus and response generalization: A stochastic model relating generalization to distance in psychological space. Psychometrika, 1957, 22, 325-345.

Shepard, R. N. Stimulus and response generalization: Deduction of the generalization gradient from a trace model. Psychological Review, 1958a, 65, 242-256.

Shepard, R. N. Stimulus and response generalization: Tests of a model relating generalization to distance in psychological space. Journal of Experimental Psychology, 1958b, 55, 509-523.

Tversky, A., and Krantz, D. H. The dimensional representation and the metric structure of similarity data. Journal of Mathematical Psychology, 1970, 7, 572-596.

OFFICE OF NAVAL RESEARCH, CODE 455
TECHNICAL REPORTS DISTRIBUTION LIST

Director, Engineering Psychology
Programs, Code 455
Office of Naval Research
800 North Quincy Street
Arlington, Va 22217 (5cys)

Defense Documentation Center
Cameron Station
Alexandria, Va 22214 (12 cys)

Dr. Robert Young, Director
Cybernetics Technology Office
Advanced Research Projects Agency
1400 Wilson Blvd.
Arlington, Va 22209

Lt. Col. Henry L. Taylor USAF
OAD (E&LS) ODDR&E
Pentagon, Room 3D129
Washington, D. C. 20301

Office of Naval Research
International Programs
Code 102IP
800 North Quincy Street
Arlington, Va 22217 (6 cys)

Director, Avionics & Weapons
Programs, Code 212
Office of Naval Research
800 North Quincy Street
Arlington, Va 22217

Director, Sensor Technology
Program, Code 222
Office of Naval Research
800 North Quincy Street
Arlington, Va 22217

Commanding Officer
ONR Branch Office
Attention: Dr. J. Lester
495 Summer Street
Boston, Ma 02210

Commanding Officer
ONR Branch Office
Attention: Dr. Charles Davis
536 South Clark Street
Chicago, Illinois 60605

Commanding Officer
ONR Branch Office
Attention: Dr. E. Gloye
1030 East Green Street
Pasadena, California 91106

Dr. M. Bertin
Office of Naval Research
Scientific Liaison Group
American Embassy, Room A-407
APO San Francisco 96503

Director, Naval Research Laboratory
Technical Information Division
Code 2627
Washington, D. C. 20375 (6 cys)

Mr. John Hill
Naval Research Laboratory
Code 5707.40
Washington, D. C. 20375

Office of the Chief of Naval
Operations, OP987P10
Personnel Logistics Plans
Department of the Navy
Washington, D. C. 20350

Director, Physiology Program
Code 441
Office of Naval Research
800 North Quincy Street
Arlington, Va 22217

Commander
Naval Air Systems Command
Human Factors Programs, AIR340F
Washington, D. C. 20361

Commander
Naval Air Systems Command
Crew Station Design
AIR 5313
Washington, D. C. 20361

Mr. T. Momiyama
Naval Air Systems Command
Advance Concepts Division
AIR 03P34
Washington, D. C. 200361

Commander
Naval Electronics Systems Command
Human Factors Engineering Branch
Code 4701
Washington, D. C. 20360

LCDR T. W. Schropp
Naval Sea Systems Command
NAVSEA 00C3
Washington, D. C. 20362

Mr. James Jenkins
Naval Sea Systems Command
NAVSEA
Code 06H1-3
Washington, D. C. 20362

Mr. Arnold Rubinstein
Naval Material Command
NAVMAT 0344
Department of the Navy
Washington, D. C. 20360

Director
Behavioral Sciences Department
Naval Medical Research Institue
Bethesda, MD 20014

Dr. George Moeller
Human Factors Engineering Branch
Submarine Medical Research Lab.
Naval Submarrne Base
Groton, Connecticut 06340

Chief,
Aerospace Psychology Division
Naval Aerospace Medical Institute
Pensacola, Fla 32512

Navy Personnel Research and
Development Center
Management Support Department
Code 210
San Diego, California 92152

Dr. Fred Muckler
Navy Personnel Research and
Development Center
Manned Systems Design, Code 311
San Diego, California 92152

LCDR Michael O'Bar
Navy Personnel Research and
Development Center
Code 305
San Diego, California 92152

Dr. James Curtin
Naval Sea Systems Command
Personnel & Training
Analyses Office
NAVSEA 074C1
Washington, D. C. 20362

LCDR R. Gibson
Bureau of Medicine & Surgery
Aerospace Psychology Branch
Code 513
Washington, D. C. 20372

CDR Paul Nelson
Naval Medical R&D Command
Code 44, Naval medical Center
Bethesda, MD 20014

Mr. Ronald A. Erickson
Human Factors Branch
Code 3175
Naval Weapons Center
China Lake, California 93555

Human Factors Section
Systems Engineering Test
Directorate
Patuxent River, MD 20670

Human Factors Division
Naval Ocean Systems Center
San Diego, California 92152

Human Factors Engineering Branch
Naval Ship Research and
Development Center
Annapolis Division
Annapolis, MD 21402

Dr. Robert French
Naval Ocean Systems Center
San Diego, California 92132

Dr. Jerry C. Lamb
Display Branch, Code TD112
Naval Underwater Systems Center
New London, Connecticut 06320

Naval Training Equipment Center
Attention: Technical Library
Orlando, Florida 32812

Mr. A. V. Anderson
Naval Personnel Research and
Development Center
Code 302
San Diego, California 92152

Human Factors Engineering Branch
Crew Systems Department
Naval Air Development Center
Johnsville
Warminster, Pa 18974

Dr. Gary Poock
Operations Research Development
Naval Postgraduate School
Monterey, California 93940

Dr. A. L. Slafkosky
Scientific Advisor
Commandant of the Marine Corps
Code RD-1
Washington, D. C. 20380

Mr. J. Barber
Headquarters, Department of the
Army, DAPE-PBR
Washington, D. C. 200546

Dr. Joseph Zeidner, Director
Organization and Systems Research
Laboratory
U. S. Army Research Institute
1100 Wilson Boulevard
Arlington, Va 22209

Technical Director
U. S. Army Human Engineering Labs.
Aberdeen Proving Ground
Aberdeen, MD 21005

U. S. Air Force Office of
Scientific Research
Life Sciences Directorate, NL
Bolling Air Force Base
Washington, D. C. 20332

Dr. Donald A. Topmill
Chief, Systems Engineering Branch
Human Engineering Division
USAF AMRL/HES
Wright-Patterson AFB, Ohio 45433

Human Factors Department
Code N215
Naval Training Equipment Center
Orlando, Florida 32813

Dr. Alfred F. Smode
Training Analysis & Evaluation
Group, Naval Training
Center, Code N-00T
Orlando, Fla 32813

Dr. W. S. Vaughan
Oceanautics, Inc.
3308 Dodge Park Road
Landover, MD 20785

Dr. Arthur I. Siegel
Applied Psychol. Services,Inc.
404 East Lancaster Street
Wayne, Pa 29087

Dr. Robert R. Mackie
Human Factors Research Inc.
Santa Barbara Research PPark
6780 Cortona Drive
Goleta, California 93017

Dr.. Gershon Weltman
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, Calif. 91364

Dr. J. W. Wulfeck
New Mexico State University
Department of Psychology
Box 5095
Las Cruces, New Mexico 88003

Air University Library
Maxwell Air Force Base
Alabama 36112

Dr. Robert Williges
Human Factors Laboratory
Virginia Polytechnic Institute
130 Whittemore Hall
Blacksburg, Va 24061

Dr. James H. Howard
Catholic University
Department of Psychology
Washington, D. C. 20064

Dr. G. H. Robinson
University of Wisconsin
Department of Industrial Eng.
1513 University Avenue
Madison, Wisconsin 53706

Mr. E. M. Connelly
Omnemii, Inc.
410 Pine Street, S. E.
Suite 200
Vienna, Va 22180

Dr. Thomas L. Harrington
University of Nevada
Department of Psychology
Reno, Nevada 89507

Dr. Robert G. Pachella
University of Michigan
Department of Psychology
330 Packard Road
Ann Arbor, Michigan 48104

Dr. H. Rudy Ramsey
Science Applications, Inc.
40 Denver Tech Center West
7935 East Prentice Avenue
Englewood, Colorado 80110

Dr. Paul Slovic
Decision Research
1201 Oak Street
Eugene, Oregon 97401

Dr. Ross L. Pepper
Naval Undersea Center
Hawaii Laboratory
P. O. Box 997
Kailua, Hawaii 96734

Journal Supplement Abstract
Service
American Psychological Assoc.
1200 17th Street, N. W.
Washington, D. C. 20036 (3 cys)

Director, Human Factors Wing
Defense & Civil Institute
of Environmental
Medicine, P.O. Box 2000
Downsville, Toronto
Ontario, CANADA

Dr. David Zaidel
Road Safety Centre
Technion City
Haifa, ISRAEL

Prof. Dr. Carl Graf Hoyos
Institute for Psychology
Technical University
8000 Munich
Arcisstr 21
FEDERAL REPUBLIC OF GERMANY

Dr. Robert Fox
Vanderbilt University
Department of Psychology
Nashville, Tennessee 37240

Dr. Jo Ann S. Kinney
Submarine Medical Research Lab.
Naval Submarine Base
Groton, Connecticut 06340

Dr. Jesse Orlansky
Institute for Defense Analyses
400 Army-Navy Drive
Arlington, Va 222002

Dr. Stanley Deutsch
Office of Life Sciences
Headquarters, NASA
600 Independence Avenue
Washington, D. C. 20546

R. W. Bryant
ASW-132, ASWPO
NAVSEA 2W28
National Center No. 1
Washington, D. C. 20360

Dr. A. D. Baddeley
Applied Psychology Unit
Medical Research Council
15 Chaucer Road
Cambridge, CB2 2EF
ENGLAND