Perception & Psychophysics
1986, 40 (6), 370-383

The multidimensional analysis of asymmetries in alphabetic confusion matrices: Evidence for global-to-local and local-to-global processing

MICHAEL R. W. DAWSON and RICHARD A. HARSHMAN
University of Western Ontario, London, Ontario, Canada

This study examined the ability of an asymmetric multidimensional scaling program (DEDICOM) to reveal information about letter-perception processes. To demonstrate its potential, we applied it to the controversy concerning local-to-global versus global-to-local letter perception. These two theories lead to different predictions about stimulus confusion asymmetries. Since DEDICOM is capable of recovering the structure of asymmetric or directional patterns, it should reveal whether a stimulus-response confusion matrix contains patterns of asymmetry more consistent with one or the other perceptual theory. This was tested using two data sets. The first (from Lupker, 1979) revealed an additive hierarchy of asymmetry strongly consistent with global-to-local processing, although unexpected additional structure and reliable anomalies indicated the need for a more refined theoretical account. The second (a full alphabetic confusion matrix combining data from Gilmore et al., 1979; Loomis, 1982; and Townsend, 1971) revealed five distinct patterns, each consisting of transformations attributable to the failure to detect specific local letter features. This solution strengthened support for local-to-global processing, in sharp contrast to the first analysis. Possible reasons for this divergence are discussed, including differences in the stimuli, exposure durations, and a hypothetical two-stage process of perception. Despite their differences, both solutions demonstrated how asymmetric scaling can reveal structure in asymmetries, which is relevant to perceptual theory and which would have been difficult to recover by other means.

The purpose of this paper is to introduce a new method of analyzing patterns of *asymmetries* in visual confusion matrices, and to demonstrate that the detailed structure of asymmetry patterns revealed by this analysis can provide important evidence concerning the type of processing used during perception. As an example, we hope to show how the analysis of "dimensional structure" of asymmetries in alphabetic confusion matrices can shed light on the global-to-local versus local-to-global nature of letter perception. In passing, we will also note how structure in the asymmetries may also be relevant to different feature-based theories of perception.

Asymmetry and Letter Perception

Let X and Y be two arbitrary cognitive or perceptual entities, and let R_{xy} be some arbitrary relationship between them (e.g., R_{xy} might be the amount that X resembles Y or the amount that X is preferred over Y). If this relationship is asymmetric, then the order in which X and Y are considered with respect to R influences the result of the comparison—R_{xy} will not lead to the same result as R_{yx}. Of particular interest in the present paper is the fact that the relationship of perceptual confusability is asymmetric. For example, in data analyzed later in this paper, it is evident that Q is mistakenly reported as O much more often than O is mistakenly reported as Q.

Confusion asymmetries can have considerable theoretical importance. One case in point is the recent controversy in the study of perception concerning the nature of the first information extracted during visual processing. Some researchers assume that global features, such as the general shape of a stimulus, become available earlier than do the more local features such as particular lines or indentations (Bouma, 1971; Coffin, 1978; Navon, 1977, 1981). This is the *global-to-local* processing hypothesis. A different perspective, the *local-to-global* processing hypothesis, assumes that visual perception involves accumulation of locally detected visual features (e.g., Lindsay & Norman, 1972; Neisser, 1967; Selfridge, 1959; Treisman & Gelade, 1980; Wolford, 1975).

Different assumptions about the nature of visual processing lead to opposite predictions about the direction of greatest stimulus confusability (e.g., Lupker, 1979). Loosely speaking, global-to-local assumptions lead to the prediction that small-envelope letters will be more

The two authors contributed equally to the work reported in this manuscript; the order of authorship is alphabetical.

Louis Goldstein, who collaborated with the second author in 1975 on development of a DEDICOM method for the analysis of stimulus confusions, has indirectly made important contributions to this paper. His work with Harshman was done before the special properties of skew-symmetric DEDICOM were well understood. Nonetheless, those early efforts (aimed specifically at the analysis of phonetic confusions) laid the groundwork for the eventual understanding that made the current paper possible. The authors would also like to thank Mark Kinnucan for insightful comments and criticisms on earlier versions of the current manuscript. This research was supported by a grant from NSERC (A7896) to the second author, and an NSERC postgraduate scholarship awarded to the first author. Send correspondence to R. Harshman, Department of Psychology, University of Western Ontario, London, Ont., Canada N6A 5C2.

frequently reported as large-envelope letters than vice versa. On the other hand, local-to-global assumptions lead to the prediction that many-featured letters will be more frequently reported as few-featured letters (see, e.g., Garner & Haun, 1978; Goldstein, 1980). These different predictions about patterns of asymmetry result from the different hypotheses about the order in which perceptual information becomes available to the subject.

Global-to-local theory. Consider a letter-identification task from the global-to-local processing perspective. Under this hypothesis, letter perception is viewed as being analogous to the gradual sharpening of focus in a camera (Navon, 1977). Early in this process, the only information available is a blurred stimulus outline, called the stimulus envelope. From this, certain global characteristics, such as the size and general shape of a letter, can be recognized, but no specific local features can be detected. Local characteristics emerge later, when the focus has sharpened sufficiently. For example, in processing the letter Q, one would first be able to detect that it was large and round; later, the tail of the Q would come into focus. Navon (1977) has supported this hypothesis by showing that the identity of a large stimulus letter that is built from many small letters becomes available sooner than do the identities of the smaller components.

As Lupker (1979) points out, the focusing metaphor of the global-to-local approach hypothesizes that "at each point in processing, the observer should have a wider array of perceptual data than is actually contained in the stimulus" (p. 306). If processing is interrupted, perfect focusing will not be achieved, and a specific kind of letter confusion will result: A subject should tend to respond to small-envelope letters as if they were large-envelope ones more often than he should to large-envelope letters as if they were small-envelope ones; because of blurring, the small-envelope stimuli will be seen as being broader than they really are.

Local-to-global theory. Perception would proceed very differently if it were accomplished by local-to-global processing. The mechanisms would build up the percept by accumulating independently perceived local letter features. For example, perceiving the letter R might involve accumulating the local features of long vertical line, raised curved line, and short diagonal line plus, presumably, information about the location of these features. Correct letter identification requires that enough stimulus features be correctly detected and located to remove stimulus ambiguities. If perceptual processing is interfered with (e.g., by short stimulus durations), then feature detection will not be perfect—some features will be missed—and incorrect identification will often result.

Feature detection failures should lead to particular patterns of asymmetries of confusions. In general, many-featured letters will be confused with few-featured letters more often than vice versa. This is because failure to detect a feature can transform a many-featured letter into a few-featured letter but cannot cause a transformation in the opposite direction. For example, R can be transformed into P by the failure to detect the feature of a short diagonal line, but no feature deletion will transform a P into an R. In addition to this general trend, the pattern of confusions should have a detailed internal structure, since particular many-featured letters will be confused only with particular few-featured ones—namely, only those that can be produced by the deletion of meaningful local features from the stimulus object. Feature-detection failure will not transform an R into a C, for example.

This is not to say that the failure to detect features is the only source of letter confusions according to the local-to-global approach; feature false alarms or ghost features can also occur (Townsend & Ashby, 1982). Furthermore, most feature accumulation models of letter perception explicitly recognize that this type of task involves both a perception stage and a decision stage (e.g., Townsend & Ashby, 1982; Wandmacher, 1976). In the decision stage, such nonperceptual factors as response bias are assumed to be relevant sources of confusion. Nevertheless, the local-to-global approach carries with it a commitment that feature detection failure will be an important and common source of error.

Testing the models. It is apparent that the two competing hypotheses can be tested empirically by studying patterns of asymmetry in confusion matrices. Unfortunately, standard analysis methods do not provide a good way to represent such patterns. Several interesting special-purpose scaling models have been recently proposed which incorporate parameters to help explain asymmetry (e.g., Bentler & Weeks, 1978; Chino, 1978; Krumhansl, 1978; Nakatani, 1972; Tobler, 1976-1977; Young, 1974; see also Keren & Baggen, 1981; Takane & Shibavama, 1985). But what is needed for our purposes is a more general method, one that can uncover and represent patterns of asymmetry in much the same way that factor analysis can uncover and represent patterns of intercorrelations among variables. In the next section a technique that solves this problem is described.

Analyzing Patterns of Asymmetry

The structure of the asymmetries in an alphabetic confusion matrix can be decomposed by a novel method of analysis called DEDICOM (for DEcomposition into DIrectional COMponents; see, e.g., Harshman, 1978; Harshman, Green, Wind, & Lundy, 1982). This method can be thought of as a generalization of multidimensional scaling (MDS) or factor analysis in that it decomposes a complex matrix into a few simple underlying patterns or dimensions. However, unlike MDS or factor analysis, it can uncover structural patterns of *asymmetric* data matrices. (Both factor analysis of covariance, or correlational data, and standard MDS of similarity data assume that $x_{ij} = x_{ji}$).

Extracting asymmetries. We will use the expression "dominance patterns" (of a confusion matrix) to refer to regularities in the asymmetries of the matrix. In order to focus on these regularities, it is helpful to separate the asymmetries in the confusion matrix from the symmetric part of the matrix. This is done as follows: Let X be the confusion matrix, with x_{ij} the entry in row i and column j (X is asymmetric if $x_{ij} \neq x_{ji}$). The symmetric part of X can be computed by averaging across the diagonal, that is, by replacing x_{ij} and x_{ji} with the average ($.5x_{ij} + .5x_{ji}$). When this symmetrized version of X is subtracted from the original X, the "pure asymmetries" are left (i.e., a matrix in which $x_{ij} = -x_{ji}$). This is called the antisymmetric, or skew symmetric, part of X, and it contains information only about asymmetries of confusions.

Representing simple patterns. When DEDICOM is applied to the antisymmetric part of a data matrix, it does not decompose the matrix into a set of one-dimensional factors or dimensions. Instead, it decomposes the matrix into a set of two-dimensional factor planes, called *bimensions* (Harshman, 1981). Each bimension represents one simple component pattern of asymmetry, just as a dimension represents one simple component pattern of symmetric relationships. (Thus, one can think of a bimension as a rank 2 analog of a dimension.) An explanation of why antisymmetric relationships require this type of representation is beyond the scope of this paper. It is related to the fact that antisymmetric relations have two aspects: a *direction* as well as a *strength*. Beyond this, we merely note that it is a mathematical property of antisymmetric relationships (see Harshman, 1981, for further discussion).

The qualitative and quantitative aspects of the pattern of asymmetric relationships captured in a single bimension can be represented geometrically, using principles first described by Gower (1977; see also Constantine & Gower, 1978). The picture, which we call a Gower diagram (Harshman, 1981), is created by plotting the location of each stimulus on the bimensional plane, as determined by its coordinates on the two axes that span that plane. The general principle used to interpret this plot is to look at areas of triangles. In particular, the strength of the asymmetric relationship between two stimuli is represented as the area of the triangle whose vertices are the positions of the two stimuli and the origin of the bimensional plane. The direction of asymmetry is represented by the order of points a and b in the triangle (or, equivalently, in the plane). By convention, the plane is drawn so that clockwise motion corresponds to a positive relationship. Thus, if stimulus a is encountered before stimulus b as one proceeds clockwise around the triangle, then the relation of a to b is positive. For example, suppose the triangle formed by the origin, a, and b has an area of five units, then R_{ab} is 5, and R_{ba} is -5.

Usually, the relationships between various pairs of stimuli will produce simple and interpretable geometric patterns. For example, when there is a single process generating the asymmetries, and all the stimuli in a particular data set participate equally in this process, the asymmetry relationships often follow a simple additive pattern ($R_{ac} = R_{ab} + R_{bc}$). If antisymmetric relations are additive in this way, the areas of the corresponding triangles must also be additive. Thus, the area of the triangle formed by the origin, a, and b plus the area of the triangle formed by the origin, b, and c must be equal to the area of the triangle formed by the origin, a, and c. This implies that the stimuli a, b, and c must lie on a straight line in the DEDICOM plot (Gower, 1977). From such linear additive dominance hierarchies, one can read off the relative dominance (asymmetry) between different stimuli simply by looking at their relative positions along the line; the distance between two points is proportional to the asymmetry between them.

On the other hand, when stimuli are involved in an asymmetric process to different degrees, their asymmetries will not be additive and the plot of the stimuli will be nonlinear. In particular, when stimulus a is reported much more often as b than vice versa, and b is reported much more often as c than vice versa, but for some reason the relationship between a and c is attenuated or symmetric, then a and c will be pulled closer to the origin of the diagram (so that their triangle will have a smaller area), and so a backward c-shaped pattern will emerge, with the a and c marking the two endpoints of the pattern.

Examples of both these patterns (and others) will be demonstrated in Study 1 and Study 2 below, where we reanalyze several previously published confusion matrices. In Study 1, we present the DEDICOM analysis of a confusion matrix involving very briefly presented letter-like stimuli; in Study 2, we present DEDICOM analyses of alphabetic confusions collected using longer stimulus durations.

STUDY 1

Lupker (1979) was interested in empirically investigating the type of processing involved during letter perception. Concerned about the confounding influence of letter feature redundancy, he created a set of 12 artificial letter-like stimuli designed to ensure that subjects could not use feature redundancy to help them guess which stimulus had been presented in the event of a feature-detection failure. He then collected eight different sets of stimulus confusion data by manipulating the time before processing was interrupted by a visual mask. To statistically remove response bias, each of the eight resulting confusion matrices was preprocessed through the application of Luce's (1963) choice model. Finally, noting that all eight matrices appeared to be very similar, Lupker collapsed them into a single overall confusion matrix. He then examined the asymmetries of confusions between selected pairs of stimuli in order to find evidence for global-to-local or local-to-global processing. The observed patterns of asymmetry supported the global-to-local model.

The purpose of our first study was to apply the DEDICOM model to Lupker's (1979) confusion matrix, to see if the details of the dominance patterns underlying these data were consistent with the global-to-local hypothesis. Some agreement was expected, since Lupker's observations had already indicated that, in his study, narrow stimuli tended to be reported as wider stimuli. However, if the details of the bimensions were consistent with Lupker's conclusions, the DEDICOM analysis would, for several reasons, provide *stronger* evidence for global-to-local processing than was possible with Lupker's analysis: First, the dominance patterns recovered by DEDICOM take into account many cells in the data matrix at once, which cannot be done in an analysis of selected stimulus pairs. This means that if the DEDICOM solution is fully consistent with global-to-local processing it will provide more comprehensive and more accurate support for the theory (indeed, the DEDICOM analysis will tell exactly what percent of the variance of the asymmetries is explained by the bimensional representation). Second, the DEDICOM dominance patterns represent more than just direction of asymmetry: they have quantitative properties as well, and these properties must also be consistent with the global-to-local hypothesis if it is to be supported. There is a range of envelope size in the stimuli constructed by Lupker. For example, X has a larger envelope than L, which in turn has a larger envelope than I. This difference in envelope size should affect the degree of asymmetry in confusions among stimuli. Specifically, narrow envelope stimuli should have more asymmetric relationships with very wide envelope stimuli than with moderately wide envelope stimuli.

Method

Data Set

The data set (from Lupker, 1979, p. 309) was a 12×12 confusion matrix for letter-like stimuli. (The stimulus shapes are presented next to the points in Figure 1.) Except for our split half analyses (see below), we will follow Lupker's procedure and consider the total confusion matrix, which gives the frequency of the various responses, combined over all 11 subjects and all eight ISI conditions. As noted earlier, the data were adjusted for response biases by means of the Luce choice model. The final matrix is based on 1,760 presentations of each stimulus.

Procedure

The antisymmetric part of the confusion matrix was computed (as explained earlier), and the DEDICOM decomposition was applied to it. The locations of the stimuli were then plotted on each recovered bimension, using the x and y coordinates generated by DEDICOM. This allowed us to represent the structure of the asymmetries geometrically. The optimal number of bimensions required to represent the dominance patterns in the matrix was chosen, in part, by performing a test similar to Cattell's (1978) scree. Four solutions, containing one through four bimensions, were computed for the matrix, and the variance accounted for by each solution was plotted as a function of the number of bimensions in the solution. The resulting curve was examined for a sharp flattening or "elbow," followed by a slowly rising straight line. (It is at this "elbow," if there is one, that most of the systematic variance in the data is accounted for.) We also paid attention to the interpretability of the solutions for each number of bimensions extracted, looking for the solution with the optimal separation of distinct interpretable dominance hierarchies without meaningless fragmentation or redundancy. Finally, the replicability of dimensions across split halves of the data was used to evaluate the statistical stability of certain bimensions (see below).

Results

Examination of the fit values indicated that only one bimension was required to represent the main features of the asymmetric patterns of the Lupker (1979) matrix. Indeed, the first bimension provided a remarkably good fit, accounting for 96% of the variance in the antisymmetric part of the data. (The symmetric and antisymmetric parts of X are orthogonal, and so contribute independent additive components to the total variance.) The squared correlations between the one- through four-bimension DEDICOM solutions and the antisymmetric part of the Lupker matrix were r^2 = .960, .986, .996, and .998, respectively. With only 12 stimuli, more than three or four bimensions are probably not feasible. Clearly most of the correlation between the DEDICOM solution and the original data involves the first recovered bimension.

One-Bimensional Solution

Figure 1a is a geometric representation (Gower diagram) of the one-bimensional solution for this data. Note that all stimuli in the solution are approximately collinear, as is indicated by the solid line in the figure. (The unfilled circle in the diagram is the origin of the bimensional plane.) As explained earlier, this type of pattern indicates that the stimuli form a "linear additive dominance hierarchy," where the distance between two stimuli along the

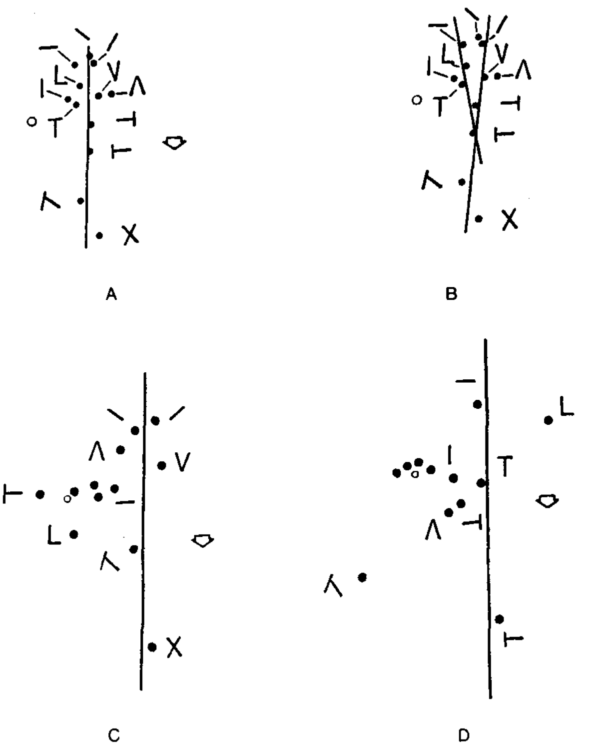

Figure 1. The results of Study 1. (a) The one-bimensional solution for the Lupker data. (b) Two possible confusion patterns in the one-bimensional solution. (c and d) The two-bimensional solution for the data.

axis of the pattern is proportional to the asymmetry between them. The nature of the hierarchy can thus be inferred from the ordering of stimuli along the line.

The linear order in Figure 1a is generally consistent with global-to-local assumptions. The direction of asymmetry, given by the arrow, shows that narrow-envelope stimuli (such as the horizontal bar) are more likely to be mistakenly identified as wide-envelope stimuli (such as the X) than vice versa. Also, the observed degree of asymmetry appears to be directly related to difference in envelope size: the more dissimilar two stimuli are in terms of envelope size, the further apart they lie in the pattern. To quantify this relationship, we created a dummy-coded size variable and correlated it with position on the line. Following Lupker's (1979) description of his stimuli, we classified these stimuli into four groups based on envelope size: very wide (the X and the oblique T), wide (the two V shapes), narrow (the T, the sideways Ts, and the L), and very narrow (the four single-feature stimuli). These four categories were dummy coded as 1, 2, 3, and 4. The perpendicular projections of the stimuli onto the main axis of the dominance hierarchy of Figure 1a were computed, and relative positions in the hierarchy were calculated by taking the distance of each projection from the most extreme projection (i.e., the projection of X). The correlation between this relative position measure and envelope size was substantial but not perfect ($r=0.71$). This provides support for the claim that the general pattern of asymmetries is related to envelope size, while suggesting that other factors may also affect confusions.

Anomalies

Indeed, inspection of Figure 1 reveals several exceptions to the general rule based on envelope size. The most striking exception is the position of the vertical bar. Instead of being clustered with the other small-sized stimuli (the horizontal and diagonal bars), it falls lower on the hierarchy along with L, V, and other middle-sized stimuli. Another anomaly is the position of the two sideways T stimuli, particularly the left-leaning T. These appear to be below the other middle-sized stimuli for no obvious reason. It is particularly difficult to explain the differences in position of the various T shapes, since these stimuli are just rotations of one another and so necessarily have the same envelope size.

Confronted with these anomalies, we must first ask ourselves whether they might be some kind of distortions introduced by the analysis. When we examine the raw data set (Lupker, 1979, p. 309), however, we find abundant evidence that these anomalies in the DEDICOM plot reflect corresponding anomalies of the data itself. For example, the stimuli that are above the vertical bar in Figure 1a do show asymmetric confusions with it in Lupker's table. They all tend to be reported as being the vertical bar more often than vice versa. This is even true for the middle-sized stimulus L, which should show the opposite direction of asymmetry according to the global-to-local theory. Furthermore, there is virtually no asymmetry between the vertical bar and the middle-sized stimuli T, V, and the upside-down V, although there should be, according to the theory. Finally, the vertical bar seems to have smaller asymmetries with the larger stimuli X and T than the other small-envelope stimuli. Similar support for the anomalous position of other stimuli, such as the left sideways T, is also provided by an examination of the data.

We conclude that DEDICOM has drawn our attention to anomalous characteristics actually present in the data, characteristics not in accord with the overall pattern or with global-to-local theory. Without the benefits of a graphical representation of the asymmetries, Lupker only noted a small part of these anomalies, and hence may have underestimated their potential theoretical significance. In particular, he pointed out (pp. 306, 308) that the vertical bar might be easily confused with the other vertical stimuli, and hence might be less perceptible (Lupker, 1979). But he did not predict, nor did he comment on, the systematic *direction* of confusion involving the vertical bar and the other small stimuli, or the reversal of the expected direction of asymmetry between it and some medium-sized stimuli. He did, however, note that the medium-sized stimuli "were perceived as the vertical line with some regularity" (p. 309). Similarly, while he predicted that the left sideways T might be less perceptible than the right sideways T (because it might be confused more with the L), he neither predicted nor noted the systematic pattern of *asymmetries* involving these sideways T stimuli, asymmetries which are not easily explained on the basis of global-to-local processing theory (e.g., the L is reported as a left sideways T 179 times, but the left sideways T is reported as an L only 138 times). Of course, Lupker is not to be faulted for this, since there are 132 different confusion frequencies to be examined and, without the benefit of the geometric DEDICOM representation, the number of *patterns* one might consider is astronomical. The ease with which we were able to discover these anomalies provides a good demonstration of the value of geometric representation of the asymmetric structure.

The second question that could be asked is whether these anomalous patterns could be attributed to chance fluctuations or whether they are reliable characteristics of the data. There are several ways of approaching this question. One could test selected individual asymmetries to see if they are too large to have arisen by chance if the population proportions were 0.5; however, this approach might fail to detect important patterns composed of many small but consistent asymmetries. Some idea of the reliability of the overall DEDICOM representation can be obtained by performing one or more split half analyses of the data. (There are also more sophisticated techniques of estimating confidence bounds around locations of stimuli, such as "bootstrapping" or "jackknifing," e.g., Weinberg, Carroll, & Cohen, 1984, but these are beyond the scope of this article.)

Since there were eight different mask delay conditions in the Lupker experiment, a split half reliability analysis can be performed by combining the 1st, 3rd, 5th, and 7th conditions into one half, and the 2nd, 4th, 6th, and 8th conditions into the other. (We thank S. J. Lupker for providing us with this unpublished data.) Separate DEDICOM analyses of these two half-data sets were performed, and they produced highly similar results. For each solution, the same linear pattern of asymmetries was observed. To quantify the degree of replication, the projections of the stimuli onto the main axis of this pattern was computed for both data sets. The correlations of these two sets of projections was 0.966, indicating a high degree of reliability. Finally, and most crucially for the current discussion, the same anomalous characteristics of the asymmetries were present in both analyses: for example, the vertical line was below the other small-envelope stimuli in the hierarchy, and the left sideways T showed the same anomalous position. Examination of the raw frequencies in the two split halves of data also confirmed that the anomalies were present in both halves. It appears that while global-to-local processing provides a general account of most asymmetries, some other perceptual influences must also be involved.

Two-Bimensional Solution

Although the one-bimensional solution provided a very good fit to the data, and could also be easily interpreted (except for the anomalies), there was evidence which suggested that another solution might provide additional structural information. In examining the overall pattern illustrated in Figure 1a, it was noted that two very obliquely related linear subpatterns of asymmetry might exist, one for stimuli consisting of horizontal or vertical feature components (called "straight" stimuli) and one for stimuli consisting of diagonal or oblique feature components (called "oblique" stimuli). These two hypothesized subpatterns are indicated by the solid lines in Figure 1b. It has been noted previously (e.g., Harshman & Lundy, 1985) that such oblique linear subpatterns might indicate that two separable bimensions had been combined into one. The two-bimensional solution for these data was therefore examined to see if these two hypothesized patterns might be represented on separate bimensional planes.

The possibility of there being more than one dominance pattern in a data matrix poses no problem for a DEDICOM analysis. The model will simply recover more than one bimension, one for each existing dominance pattern. Stimulus objects not involved in a particular pattern will not load on the bimension representing that pattern (i.e., they will fall near its origin). Of course, some aspects of the analysis do become more complicated when more than one bimension can be recovered. In particular, one has to consider alternative descriptions obtainable by taking different linear combinations of a given set of bimensions. For convenience, we describe this as rotation of different bimensions in the solution. DEDICOM can rotate bimensions to different positions (alternative linear combinations) in a manner similar to the rotation of factors in factor analysis, and similar considerations of simple structure can be used to choose a preferred rotation. Much of DEDICOM's ability to summarize patterns of asymmetry stems from the properties of these rotations. (In all the solutions reported in this article, we use analytic rotations that are similar to VARIMAX but which operate on two pairs of axes at a time and allow oblique bimensions; the method is a planewise modification of Harris and Kaiser's [1964] "Orthoblique" transformation method. For a more detailed discussion, see Harshman, 1981.)

The two bimensions obtained from the second analysis are presented in Figures 1c and 1d. Together, these bimensions account for 98.6% of the variance of the antisymmetric part of the data. Although this is not a great increase from 96%, fit values were already close to the ceiling and so had little room for improvement. The small size of the increase does not mean that the second rotated bimension contributes little variance. After rotation, the variance is distributed more evenly between the two bimensions.

Despite the modest increment in variance-accounted-for, the two-bimensional representation was reasonably reliable, as indicated by its replication across the split halves of the data. When we projected each axis of the even split half into the corresponding bimension of the odd split half (by using multiple regression), we obtained multiple R values of 0.95 and 0.96 for the axes of Bimension 1 and 0.94 and 0.94 for the axes of Bimension 2. The corresponding projections from the odd into the even split half yielded multiple Rs of 0.94, 0.96, 0.94, and 0.94. The split into two bimensions was also highly interpretable, reflecting (as predicted) the distinction between oblique and straight stimuli.

Bimension 1, presented in Figure 1c, represents the pattern of asymmetry among oblique stimuli. Global-to-local processes are apparent here, since the vertical positions of these stimuli (their projections on the major axis of the bimension) closely resemble their vertical positions in the one-bimensional solution (Figure 1a); in fact, they have exactly the same rank order. The straight stimuli, on the other hand, have almost no vertical dispersion on this bimension, and so none of the asymmetric relationships among these stimuli are represented in this plane. They are also closer to the origin than any of the oblique stimuli, and fall to the left of the oblique stimuli in the plane. Thus they generate only small triangles, and hence small asymmetries, with the oblique stimuli within this plane. (The bulk of asymmetric confusions between straight and oblique sets is accounted for by the obliqueness of the two bimensions.)

Bimension 2, presented in Figure 1d, complements Bimension 1. It primarily represents the confusions among the straight stimuli. In this bimension, it is the straight stimuli that have a wide range of vertical positions which closely resemble those in the one-bimensional solution (falling in exactly the same rank order), and it is the oblique stimuli that have little vertical dispersion. All the oblique stimuli fall to the left of the straight stimuli, and, with the exception of the oblique T and perhaps the upside-down V, are clustered close to the origin.

There are, however, two extra features of Figure 1d that should be noted. First, there is an oblique stimulus, the oblique T, which does not lie close to the origin. But because of its position at the far left, the only substantial triangle that it generates is with respect to the left-leaning T (and perhaps, to a lesser extent, the L). We speculate that this anomaly in the pattern is due to the special confusion between the oblique T and the left-leaning T. Second, the L protrudes a bit to the right of the linear dominance hierarchy. This is probably because of extra confusion between it and the left-leaning T. These two extra patterns of confusion are presumably included in this plane because there is nowhere else for them to go. If we were working with a larger stimulus set, it might have been feasible to extract more bimensions, and perhaps isolate these extra sources of confusion asymmetry into a separate plane or planes, leaving the second bimension a more "pure" expression of the global-to-local processes involving straight stimuli.

Discussion

The general result of the first study was that the DEDICOM analysis of the Lupker (1979) confusion matrix revealed an overall dominance pattern that strongly supported his global-to-local processing interpretation. This support was both qualitative and quantitative, and accounted for almost all of the asymmetric variance in the data. Thus, in some ways, this result is even stronger than Lupker's own evidence supporting a global-to-local interpretation of this data.

The linear structure of the pattern of asymmetries in the one-bimensional solution is quite striking. As noted earlier, this implies that the asymmetry in stimulus confusions followed a simple additive pattern, in which the asymmetry between stimuli *a* and *b* plus the asymmetry between stimuli *b* and *c* gives a good estimate of the asymmetry between stimuli *a* and *c*. Since differences in envelope size also have this additive property, the simple form of the one-bimensional solution is consistent with the interpretation that envelope size is the main stimulus characteristic producing confusion asymmetries.

Although the linear pattern in Figure 1a indicates that global-to-local processing is being applied to all stimuli, the results depicted in Figures 1c and 1d suggest that envelope size is not the only factor influencing asymmetry of stimulus confusions. The fact that the confusion asymmetries were decomposed into two different (although admittedly nonorthogonal) bimensions indicates that there were stronger asymmetries *within* the two groups of oblique and straight stimuli than *between* these two groups of stimuli.

The global-to-local hypothesis does not predict this clustering of asymmetries, at least when formulated in terms of a simple focusing metaphor, as in Lupker (1979). Such clustering seems more compatible with a featural account. Furthermore, the sort of feature that seems to distinguish the two subsets of stimuli is quite different from the local pieces of a stimulus (such as the tail of a Q or the bar of an F) that we will encounter in Study 2. Instead, it seems related to the orientation of high-frequency information in the stimulus. This might suggest that the global-to-local account should be integrated with a spatial filter account that incorporates direction (phase) information, or perhaps the effect is related to evidence that the human visual system processes oblique and straight stimuli differently (e.g., Apelle, 1972).

In addition to the two-bimensional structure, there are problems posed by the reliable anomalies in the hierarchical order of the asymmetries (e.g., with respect to the vertical line and the sideways Ts). It becomes apparent that there is more to the structure of Lupker's data than predicted by the simplest form of global-to-local theory. It is not clear whether an adequate account of these data will require trivial or substantial alterations of the theory. By themselves, the anomalies might merely suggest, for example, that preprocessing via Luce's choice model was not quite appropriate. But considered together with the two-bimensional structure, the results seem to indicate that the global-to-local processing model needs to be refined by the addition of more precise processing theory and/or specific decision rules (e.g., ones that would somehow be sensitive to stimulus obliquity).

The structure newly revealed by DEDICOM should act both as a stimulus to further research and as a constraint on process models that might grow out of that research. In this article, however, our focus is on the DEDICOM methodology and what it can uncover, and so we leave the development of revised global-to-local accounts of these data to others.

STUDY 2

The purpose of Study 2 was to apply DEDICOM to alphabetic confusion matrices that have appeared in the literature. We were particularly interested to see if the dominance patterns recovered from such data could be interpreted as supporting either global-to-local or local-to-global perceptual processing. We were also interested in seeing how DEDICOM would represent the more complex patterns of asymmetry that might arise with 26 different letters as the stimulus and response set.

Method

Data Sets

Three different full alphabetic confusion matrices were examined. The first was taken from Condition I of Townsend (1971). Townsend obtained this matrix by tachistoscopically presenting uppercase letters printed using an IBM typewriter; each stimulus was presented 150 times across subjects. The second matrix was taken from Loomis (1982). He presented uppercase letters to which low-pass spatial filtering had been applied. Each stimulus was presented 1,476 times across subjects. The third confusion matrix was taken from Gilmore, Hersh, Caramazza, and Griffin (1979). They used a fast-decay phosphor screen to display dot matrix uppercase letters, presenting each stimulus 1,200 times across subjects.

Procedure

Averaging. An average confusion matrix was created from the three data sets described above. All matrices were converted to proportions of responses, and were equally weighted in the averaging process. This averaging was done to improve the reliability and the generalizability of the patterns in the data. It was thought that conclusions based on the structure of the average matrix would be somewhat less subject to idiosyncratic methodological influences that can affect obtained confusions (e.g., Gilmore & Hersh, 1979; Mewhort & Dow, 1979). To ensure that the averaging process did not introduce patterns of structures not observed in any of the individual matrices, DEDICOM was also applied to each of these data sets individually, and comparisons between these results and the results of analyzing the average matrix were made. Since we wanted to allow for confusions between, as well as within, the subsets represented by different bimensions, we again used oblique "planewise" transformations to obtain the final solutions.

Response bias. Unlike the published data analyzed in Study 1, the three published data sets analyzed in Study 2 were not preprocessed with Luce's (1963) choice model to remove the effects of response bias. We wanted to look at the same data that those authors considered, to facilitate comparisons between our findings and theirs, and so did not want to adjust these published data sets ourselves. It is therefore important to consider what asymmetries might be introduced by response bias. In letter-recognition experiments, subjects are expected to make a letter identification on every trial. In trials in which a great deal of stimulus information is not detected, the percept may not resemble *any* particular letter. Faced with this situation, subjects would have to guess the identity of the stimulus according to some strategy. For instance, subjects might be inclined to guess stimulus identities by using their tacit knowledge of the frequency of letter occurrences—giving the names of common letters with greater frequency than the names of uncommon letters. This type of strategy would reveal itself in a very systematic pattern of confusion asymmetries: less common letters would be mistakenly identified as more common letters more often than vice versa. Since response bias was not extracted from these three data sets before analysis, we decided to cope with its potential influence after the analysis, by careful consideration of its possible influence on the observed patterns.

Results

When DEDICOM was applied to the antisymmetric part of the average confusion matrix, five interpretable bimensions were recovered. The squared correlations between the DEDICOM solutions and the input data for the first five solutions were 0.45, 0.64, 0.79, 0.86, and 0.87. Figure 2 presents the geometric representation of the five bimensions obtained in the analysis. In these figures, an unfilled circle represents the origin of a bimensional plane, and solid lines illustrate dominant patterns of asymmetry. The arrows indicate the direction of the asymmetry in the same manner as in Figure 1. For these planes, letters that had a loading less than or equal to ± 0.10 on *both* axes of the plane were not drawn. This was done to reduce crowding on the plot, and was appropriate because these letters had a very small degree of participation in the pattern represented in the bimension, and so were not considered when the pattern was interpreted.

Before considering the DEDICOM plots in detail, we should point out that the interpretations will not be as directly determined by the output as would be the case if we were fitting a specific process model, with a predetermined feature set and decision rule. When fitting a fixed theoretical model, one simply examines the estimated parameter values and the fit of the model to the data. DEDICOM, on the other hand, is more theoretically neutral; it simply displays the patterns in the data. Therefore, interpretation of the bimensions involves a search for the most plausible theoretical account of the statistical regularities revealed by the program. This is the same process that one would use to interpret factors in a factor analysis, or dimensions and stimulus configurations in an MDS analysis.

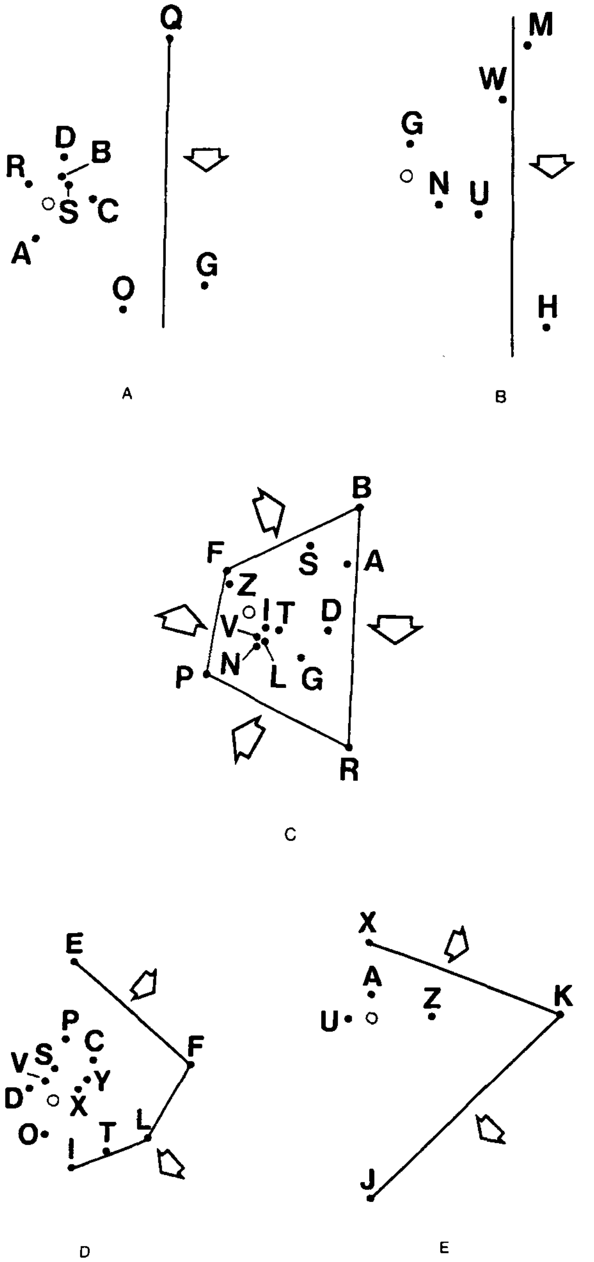

Figure 2. The five bimensions recovered from the average alphabetic confusion matrix. See text for explanation.

Consequently, we do not start with a preconceived feature set and interpret the asymmetries in terms of loss or gain of these features. We examine the plots to determine what features and what decision rule(s) might give a plausible account of the patterns in the data. Furthermore, the same DEDICOM results could subsequently be used by other investigators as the basis for a different theory, provided theirs could give a better account of the features in the plot. DEDICOM plots, like the data themselves, represent evidence rather than conclusions.

Examination of the plots (Figures 2a to 2e) suggests to us that the most convincing account of these regularities would probably be in terms of local features, corresponding to stimulus parts (e.g., the tail of the Q). Along with such features, we need to postulate a decision rule more or less like the following: When the subject detects a set of features, he/she guesses the letter that contains the entire set of perceived features and as few other features as possible.[1] With such features and decision rules, the patterns on most of the plots seem to make a great deal of sense.

In the following discussion, however, we do not assume or claim to know exactly what the feature set was, nor do we work out nuances of our presumed decision rule (if any are needed), both because it is unnecessary for our present purposes and because we think that this is best left to others who we hope will use these results to formulate new process models. Even with the somewhat loosely stated feature types and decision rules that we assume, it seems clear that data in Study 2 give a sharply different impression of perceptual processing from that suggested by the data in Study 1. We doubt that there are any plausible variations in the hypothesized stimulus features or decision rule that could account for these patterns yet markedly change the overall conclusion.

Figure 2a illustrates the first bimension taken from the data. This bimension appeared to capture confusion asymmetries among letters that were predominantly round. The direction of asymmetry in the pattern was from many-featured stimuli to few-featured stimuli, and was therefore consistent with local-to-global processing assumptions. The largest asymmetries involved Q, which was mistakenly reported as O or G or C more often than the reverse. Since Q can easily be transformed into O by the failure to detect its tail, and can also be easily transformed into G or C by the failure to detect parts of its curve, these patterns are consistent with the local-to-global hypothesis that letter confusions are due to the failure to accumulate or detect all of the relevant local letter features. However, these results are also consistent with a guessing strategy interpretation. The single-letter frequency norms of Mayzner and Tresselt (1965) show that the letter Q is many times less frequent than the letters O, G, and C; this pattern may therefore represent an asymmetry among round letters that indicates a tendency to generate more familiar letter names. This alternative interpretation is also supported by noting the small asymmetry from C to O in this pattern, which is contrary to local-to-global predictions but consistent with a guessing interpretation since C is approximately three times less common than O.

Bimension 2 is represented in Figure 2b. This pattern of asymmetries appears to be among "boxy" letters that consist of two lateral vertical line segments joined by some other features. The observed pattern is again consistent with local-to-global predictions, as the direction of asymmetry is from the many-featured stimuli M and W to the few-featured stimuli H, N, and U. The largest asymmetry is from M or W to H. This type of confusion can be viewed as an approximate transformation that is quite likely to occur when the central features of M and W are not detected. The confusions of M and W with N and U can also be explained in this fashion. Again, these results are roughly consistent with the guessing strategy interpretation. The Mayzner and Tresselt (1965) norms indicate that M, W, and U are all approximately equally frequent in written English, and all three are about half as frequent as H.

Bimension 3 is depicted in Figure 2c. This bimension generally appears to capture asymmetric confusion relationships between letters that consist of a vertical and a curved feature. The largest pattern represented are the confusions from B to R to P, which is easily accounted for in terms of feature-detection failure. The positioning of other stimuli in this bimension is also consistent with a local-to-global perspective. For example, L and D (and to some extent G, A, and T) could be considered to be feature subsets of B, and so are likely misidentifications when some of the features of B are not detected. But, once again, there is also some "noise" in this interpretation, as the positioning of N and S is not easily explained. This pattern is not, in general, consistent with a guessing bias interpretation, since R is approximately four times more frequent than P or F.

Figure 2c demonstrates two additional interesting features. First, the asymmetry pattern is not linear. In general, curved asymmetry patterns generated by DEDICOM arise because the process that produces the asymmetry between two similar stimuli (which are near each other in the pattern) cannot be applied as efficiently to two stimuli that are dissimilar and far apart in the pattern (Harshman & Lundy, 1985). In Figure 2c, this would mean that confusion asymmetries between letters that differ by one or two features (e.g., B and R) are more likely to occur than confusion asymmetries between letters that differ by many features (e.g., B and L, or R and F). The second interesting property of this pattern is its circular nature. Although the asymmetry "flows" from B to P, it turns full circle and the asymmetry "flows" back to B from the letters Z and F. This characteristic of the pattern is not consistent with the local-to-global interpretation of the data, but might be the result of some "noise" introduced by a guessing strategy. The Mayzner and Tresselt (1965) letter-frequency norms indicate that Z is the least frequent letter in English; it is perhaps no coinci dence that it marks the point at which the pattern turns back on its origin. There is one final puzzle: the asymmetry between F and B is consistent neither with a local-to-global nor with a guessing strategy interpretation. F has fewer features than B and is slightly more frequent.

Bimension 4 (Figure 2d) appears to predominantly represent confusion asymmetries among letters consisting of horizontal and vertical components. The pattern of these asymmetries is quite consistent with the local-to-global interpretation, since it demonstrates the progressive transformation of E to F, T, L, and I, which can be accounted for in terms of the failure to detect the presence and/or location of horizontal features. Once again, this pattern is curved, indicating that transformations due to the failure to detect one feature are more likely than transformations due to the simultaneous failure to detect several features. This pattern is completely inconsistent with a guessing strategy interpretation; E is by far the most common letter in written English, yet in this pattern it is confused with several other letters much more often than they are confused with it.

Bimension 5 (Figure 2e) was actually the third bimension to emerge from the analysis, but was left to last because it is so hard to interpret. Although there is some visual similarity between X and K, since a loss of information about the left-side diagonals of X could result in a mistaken report of K, the basis for confusions between K and J is not apparent. Nonetheless, this pattern is not an artifact of the DEDICOM analysis, since it is actually present in the raw data (in our combined data matrix, K was reported as J 13.2% of the time, while J was reported as K only 6% of the time). This asymmetry cannot be attributed to guessing biases based on letter frequency, since K is almost nine times more frequent than J. In short, we do not know how to explain this feature of the data. However, an examination of the three component data sets individually shows that this peculiar asymmetry appears only in the Gilmore et al. (1979) data. Thus it may be due to some idiosyncratic aspect of that particular study.

Average versus Individual Solutions

An additional concern of ours was the effect of the averaging process on the asymmetric patterns revealed in the analyses. It was possible that the averaging process produced spurious patterns or destroyed systematic asymmetries present in the individual data sets. To examine this possibility, each of the three original matrices was individually analyzed with DEDICOM. In general, the results were similar to those obtained with the averaged matrix. Versions of the patterns represented in Figures 2a and 2b were found in all three individual confusion matrices. The pattern represented in Figure 2c was found in the Gilmore data, and the pattern in Figure 2d was evident in the Townsend data. The asymmetries represented in Figure 2e, which are difficult to interpret, were present in the Gilmore data.

Discussion

The results of Study 2 provide relatively strong support for the local-to-global approach. In all of the bimensions, many-featured stimuli were more likely mistakenly identified as few-featured stimuli than vice versa. Also, very specific confusion patterns were found to exist. Confusions within each bimension appeared to be best described in terms of the failure to detect specific local features of stimuli, such as the tail of the Q, the obliques of M and W, and the horizontal bars of E. Different bimensions accounted for different stimulus types; for example, Bimension 1 represented confusions among round stimuli, while Bimension 2 represented confusions among boxy stimuli. A stimulus with a high loading on one bimension did not, in general, have a very high loading on any other bimension. This pattern is consistent with the local-to-global perspective, because it is difficult to confuse one letter type (e.g., a round letter) with another letter type (e.g., a boxy letter) by failing to detect a stimulus feature. Hence letters of different types should not have high loadings on the same bimension. (Of course, there will still be *some* confusions across different stimulus types. In our DEDICOM solutions, this is taken care of by the obliqueness of the bimensions.)

Several of the confusion patterns observed in these data were backward C-shaped. This tells us something about the relative asymmetry of confusions involving one, two, and more features. The curvature indicates that asymmetries in these probabilities are not additive. That is, the asymmetry in probability of a two-feature confusion is not the sum of the single-feature asymmetries. This pattern further demonstrates the fundamental differences in asymmetric structure between Study 2 and Study 1. The structure of confusion asymmetries in Study 2 is more consistent with an account in terms of discrete units, whereas the pattern in Study 1 is more consistent with variations in an analog property (such as size).

Although the Study 2 results were in general consistent with local-to-global processing, some specific inconsistencies were noted. In some cases, relatively large confusion asymmetries were found to exist between stimuli that were at best only approximately similar (e.g., Q and A). It was suggested that these were possibly due to nonperceptual factors, such as decision processes used by subjects, or to the averaging together of data sets obtained from slightly different experimental procedures. Overall, however, the DEDICOM solutions were quite interpretable, which is gratifying, given the nature of the raw data. With alphabetic confusion matrices, the large stimulus set and the attempt to maintain a 50% error rate leads to fairly small entries in the many off-diagonal cells of the matrix.

One of the difficulties with local-to-global theories of letter perception is that it has been very difficult to empirically establish the feature set used by the visual system (e.g., Townsend, 1971). Although traditional scaling analyses of the symmetric component of alphabetic confusion matrices have revealed global letter features (e.g., roundness, straightness, and so on), these analyses have not revealed more specific local features (e.g., the tail of a Q). At the level of distinct bimensions, this was also true of the DEDICOM analyses of Study 2. The five different bimensions appeared to represent asymmetric patterns among letters that had similar global structure (e.g., asymmetries among round letters, asymmetries among straight letters, and so on). However, the specific patterns within each bimension provided detailed information about factors affecting asymmetry which appeared to reflect the processing of specific local letter features. In particular, the best account of most of the bimensions was in terms of the failure to detect specific local letter features. Thus, the DEDICOM analysis provided more evidence for local-to-global processing than had been obtained in previous studies using more traditional scaling techniques.

In spite of this, one still might question how much additional information the DEDICOM analysis revealed. It has long been known that there is a tendency for complicated stimuli to be mistakenly reported as simpler stimuli more often than vice versa (e.g., Garner & Haun, 1978; Geyer & Dewald, 1973; Wandmacher, 1976). It could be argued that the bimensions described in Study 2 simply reiterate this point. We would argue, however, that this is not the case. First, if the patterns of asymmetry were due *only* to differences in stimulus complexity, then one would expect to recover a single bimension. Presumably, this bimension would be a linear dominance hierarchy, and the position of each stimulus within this hierarchy would be a function of the complexity of the stimulus. The fact that we recovered more than one bimension, and that different bimensions could be distinguished by noting characteristics of the stimuli that they represented, suggests that stimulus complexity is not the only factor affecting confusion asymmetries. Second, many of the confusion patterns recovered were curvilinear. This is much more consistent with an account of confusions based on the failure to detect distinct local properties (i.e., features) than with an account based on differences in the level of a single property (i.e., complexity). And third, by examination of the patterns of asymmetry within bimensions, evidence for specific local features can be uncovered. In short, while the DEDICOM analysis is consistent with the previous claims about confusion asymmetries and stimulus complexity, it provides additional information suggesting that an undifferentiated stimulus complexity account is not sufficient to explain all of the patterns of asymmetry.

GENERAL DISCUSSION

Alphabetic confusion matrices have traditionally been analyzed using techniques such as cluster analysis, factor analysis, or multidimensional scaling. The goal of such analyses, which are generally insensitive to asymmetry, has been to discover the dimensions along which letters are treated as similar by the visual system (e.g., Geyer & Dewald, 1973). In certain respects, this goal has proven difficult to achieve. In many cases, dimensions obtained from the analysis of empirically obtained confusion matrices reveal patterns of similarity related to general characteristics of letters, such as their roundness or straightness, but do not often reveal patterns related to specific local featural properties (e.g., Gilmore et al., 1979; Künnapas, 1966; Loomis, 1982; Townsend, 1971). This is not to say that these traditional types of analysis have not been productive (cf. Keren & Baggen, 1981). Our point is that these traditional types of analyses have not provided strong enough evidence to make a convincing case for feature-based models of letter perception.

The results of Study 1 and Study 2, reported above, indicate that the multidimensional analysis of *asymmetries* in an alphabetic confusion matrix may provide a rich new source of information about letter confusion, as well as about the dynamic processes involved in letter perception. Within each study, DEDICOM revealed highly systematic and interpretable regularities in the asymmetries. The details of these patterns both strengthened and qualified the conclusions that had been drawn by previous investigators.

The greatest puzzle was the profound conflict between the patterns of asymmetries in the two studies. In both cases, the DEDICOM analysis brought out novel characteristics of the data that actually strengthened the prior interpretations. In the Lupker data, DEDICOM quantified the percentage of the antisymmetric variance that could be explained by a stimulus confusion hierarchy going from smaller to larger stimuli, and it turned out to be quite high (96%). Furthermore, it showed that the strength of the asymmetry was systematically related to the difference in envelope size (anomalies aside). Thus, DEDICOM's ability to represent quantitative relationships among many simultaneous asymmetries turned out to be important. The linear additive pattern of asymmetry sizes, as indicated by the linear DEDICOM plot, was a new piece of evidence for Lupker's general conclusion. It indicated that in Lupker's data the asymmetries obeyed a quantitative rule that would not generally be expected from feature-based accounts, but which is consistent with an account in terms of an analog property—difference in envelope size.

In Study 2, DEDICOM strengthened the contrary conclusion by revealing new characteristics of the asymmetries which were consistent with a local-to-global interpretation. Subsets of apparently similar stimuli participated in asymmetric subpatterns of confusion. Stimuli loading on any single bimension seemed to have similar feature compositions, and their ordering on the bimension was easily interpreted in terms of the number of features possessed, thus suggesting that failure to detect specific local features was the predominant source of confusion asymmetries. Even the "curvature" of the patterns in each bimension was consistent with what one would expect on the basis of accumulation or loss of partially independent features. Thus, the quantitative relationships among different asymmetries turned out to be consistent with the simple qualitative picture obtained by prior researchers.

Instead of resolving the apparent contradiction between the two data sets, DEDICOM analysis has made the contradiction even more acute. The DEDICOM results further persuade us, if such persuasion were needed, that neither set of evidence can be easily explained away. Instead, both must be embraced in some larger explanatory framework.

We are not sure of how best to explain the inconsistency between Study 1 and Study 2. There are several differences between them that might turn out to be relevant. Lupker (1979) used letter-like stimuli instead of letters, fewer stimuli, quite short stimulus durations, and stimulus masks. However, since we are unable to dismiss the patterns in either data set as resulting from some artifact, we are left with the tentative conclusion that both global-to-local and local-to-global processing can occur.

One possible explanation, for example, is that simpler stimuli such as Lupker's are more likely to elicit an initially global perceptual strategy, particularly if some of them are unfamiliar. On the other hand, more complex stimuli which are less easily differentiated on the basis of global shape might stimulate a local-to-global approach, particularly if the features are highly familiar or even overlearned (see also Ward, 1982).

Alternatively, global-to-local and local-to-global processing might be two stages of a common perceptual process. Very early processing in letter perception might consist of the focusing of stimulus letters to the point at which local letter features become available. Then feature sampling or accumulation mechanisms might begin operating in order to analyze the focused percept in an attempt to identify the stimulus. Since most of the stimulus durations in the Lupker (1979) experiment are much shorter than the stimulus durations used to obtain the other three data sets analyzed, it is possible that Lupker's data provides information about early, global-to-local visual processing, whereas the other experiments captured confusions in the later local-to-global stage. (However, our attempts to confirm this by separately analyzing shorter versus longer duration conditions of the Lupker data were unsuccessful. No reversal of asymmetries was apparent.)

The notion that perception might first be global-to-local and then be local-to-global is not new. For example, Townsend, Hu, and Evans (1984) use this two-stage processing account to explain why some feature-processing models can provide good fits to empirical data even when important assumptions underlying these models have been violated. This dual processing notion also emerges in Marr and Hildreth's (1980) theory of early visual processing. In this theory, several filters of different spatial frequencies are first used to detect sudden intensity changes in the gray level image. The operation of these filters can be described in terms of the focusing metaphor, because the results of low-frequency filters are used to determine whether higher frequency filters are detecting scene information or are, instead, just detecting noise. The results of this processing is then organized into a symbolic map (the primal sketch) that represents the locations of features like thin bars and small blobs of different orientations. Later figure-oriented processes (e.g., processes that find contours through feature aggregation) can use this representation as input.

Other researchers have attempted to account for confusion asymmetries at a higher, or more cognitive, level, on the basis of hypothesized properties of letter representations (Appelman & Mayzner, 1982; Keren & Baggen, 1981; Krumhansl, 1982). In these accounts, letter confusion asymmetries are due either to differences in the salience of features in the letter representations (cf. Tversky, 1977) or to differences in the distinctiveness of one letter compared with another defined in terms of density of surrounding stimuli in a representational space (Krumhansl, 1978). Our results show that a nonrepresentational account of observed asymmetries may also be possible; explanations in terms of the direction of visual processing may provide an account of many details of the asymmetric patterns revealed by the DEDICOM analysis.

DEDICOM and Alternative Approaches

A common practice in the literature has been to fit observed alphabetic confusion matrices with mathematical models that vary in terms of assumed processing details (e.g., Townsend, 1971). The fit of the model to the empirical data is a measure of its validity. In more recent experiments, specific processing assumptions of these mathematical models have been explicitly tested (e.g., Townsend & Ashby, 1982; Townsend, Hu, & Ashby, 1980; Wandmacher, 1976). In this type of experiment, subjects are usually asked to identify perceived features as well as to identify the presented stimulus. This has allowed researchers to test assumptions about whether different features are detected independently, whether a single feature is equally detectable in all stimuli in which it appears, and so on.

DEDICOM is not a mathematical model of perception in the sense described above. It does not require detailed assumptions about the perceptual processes involved in creating a particular data set. Instead, it is concerned with revealing any patterns in the data. In other words, it is concerned with making explicit certain structural aspects of a data set that might later be useful for developing more specific perceptual models. Thus it is best viewed as a statistical analysis technique.

Response Bias

Our objective in this article has been to demonstrate the value of the multidimensional analysis of the asymmetries in stimulus confusion matrices. To this end, we have taken the same data used in several published studies, and reanalyzed it to show how additional information can be revealed. This led us in Study 1 to use Lupker's (1979) idealized confusion matrices—which have been preprocessed by the choice model to remove column biases—and in Study 2, a combination of Townsend's (1971), Loomis's (1982), and Gilmore et al.'s (1979) alphabetic confusion matrices—which were *not* preprocessed to remove response biases. In both cases, DEDICOM revealed additional meaningful structure in the data. However, we are not ourselves endorsing either approach to response bias.

The question of column biases becomes a particularly problematic one when one is interested in the asymmetries in a matrix. The popular method of applying the Luce (1963) choice model in essence assumes that the perceptual process generates symmetric confusions, and so tries to find bias terms that will remove as much of the observed asymmetry as possible. As a result, the estimated bias terms absorb *too much* of the asymmetry, incorporating some of the asymmetry arising from perceptual processes (such as the failure to detect local features) along with whatever asymmetry might arise from response processes such as guessing biases (Keren & Baggen, 1981). An interesting discussion of problems with the interpretation of the bias terms (and a very useful survey of models for stimulus confusion data) can be found in Takane and Shibavama (1985).

However, it is not optimal just to ignore the potential effects of guessing or other response biases. One might analyze the uncorrected data and simply try to take possible response biases into account, as we did in Study 2, or one might try to estimate response biases in a more sophisticated fashion, one that does not assume that bias-free data would be symmetric. Indeed, a version of DEDICOM has been formulated which would estimate column bias terms as well as the bimensional structure of the data (Harshman, 1980). This might ultimately be the best approach, but it has not yet been programmed.

Conclusion

We have shown that a multivariate analysis of the asymmetry in alphabetic confusion matrices is a potentially useful new source of information about letter-perception processes. It has revealed patterns in the asymmetries of published data sets that would seem to call for further refinements of process models developed to explain these data. Some aspects of the newly uncovered structure might serve to constrain potential models of letter perception. Our hope is that this procedure will be used to complement other approaches, both statistical and theoretical, that have been applied in this domain.

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NOTE

1. We thank one of the anonymous reviewers for pointing out the desirability of making explicit the type of feature set and decision rule we were assuming.

(Manuscript received March 31, 1986;
revision accepted for publication September 3, 1986.)