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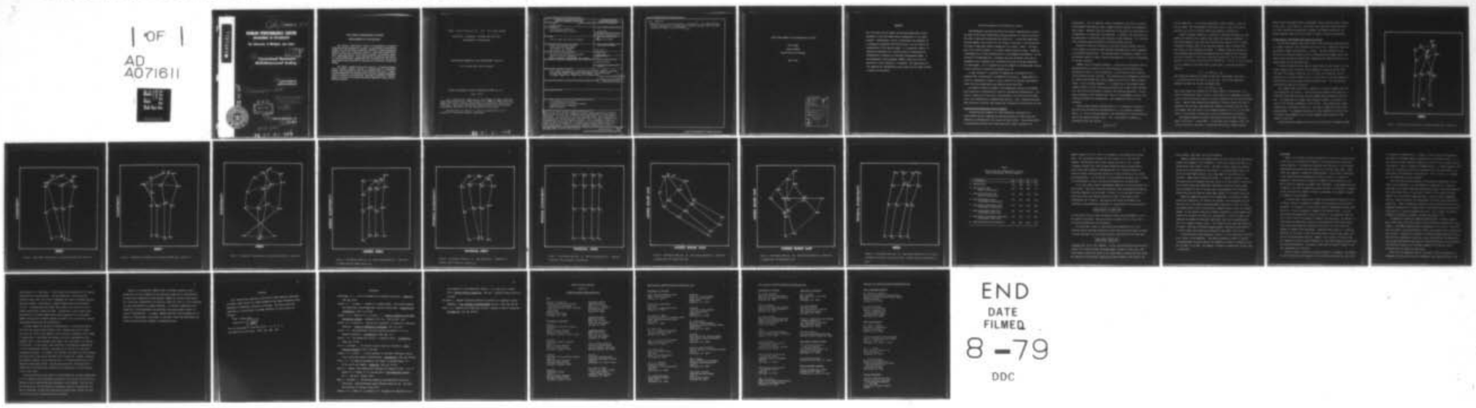

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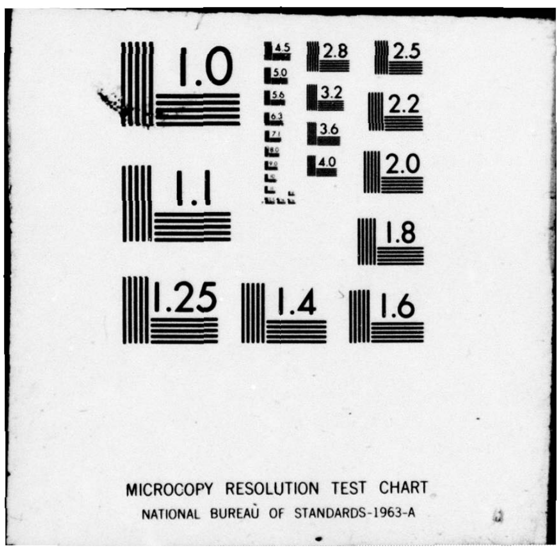
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CONSTRAINED NONMETRIC MULTIDIMENSIONAL SCALING

Elliot Noma AND Janice Johnson

HUMAN PERFORMANCE CENTER TECHNICAL REPORT NO. 62

June, 1979

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One of the most crucial aspects of most multidimensional scaling procedures is that the lowest-stress configuration is the output produced. Unfortunately, little is known about the uniqueness of a configuration generated from fallible data, yet this affects the interpretation of the spatial output. It is possible, however, to examine the uniqueness of a scaled solution by constraining the configuration to conform to a particular psychological model. A multidimensional scaling program, CONSCAL, which will allow the

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imposition of such constraints, is proposed. The implications of this approach for interpreting scaling outputs and for model testing in general are discussed.

Constrained Nonmetric Multidimensional Scaling[1]

Elliot Noma

Janice Johnson

The University of Michigan

March 1979

Abstract

One of the most crucial aspects of most multidimensional scaling procedures is that the lowest-stress configuration is the output produced. Unfortunately, little is known about the uniqueness of a configuration generated from fallible data, yet this affects the interpretation of the spatial output. It is possible, however, to examine the uniqueness of a scaled solution by constraining the configuration to conform to a particular psychological model. A multidimensional scaling program, CONSCAL, which will allow the imposition of such constraints, is proposed. The implications of this approach for interpreting scaling outputs and for model testing in general are discussed.

Constrained Nonmetric Multidimensional Scaling

Multidimensional scaling algorithms yield spatial representations in which the order of the scaled interstimulus distances matches, as closely as possible, the order of observed interstimulus dissimilarities. In most multidimensional scaling programs, the criterion for "as closely as possible" is the minimization of stress or some other index of goodness-of-fit (Kruskal, 1964a). The major goal of all scaling, however, is to reveal latent structure in data. Therefore, interpretability of scaled configurations is the paramount consideration. By the criterion of interpretability, a procedure that only minimizes stress may be inadequate since a minimum-stress configuration may not be the most meaningful or interpretable. This is especially true for nonmetric multidimensional scaling, in which statistical guidelines are generally ad hoc.

In some instances it is possible to enhance the interpretability of a minimum-stress configuration by systematically altering it. Though there will often be a concomitant increase in stress, selection of the more interpretable rather than the minimum-stress configuration may be justified.

We propose a method for nonmetric multidimensional scaling called CONSCAL, which constrains a configuration to satisfy a prespecified interpretation. This permits a comparison of the stress value obtained in this way with the minimum stress value (obtained by an unconstrained scaling). Such a comparison provides some indication of how well the prespecified interpretation characterizes the data.

Constrained Multidimensional Scaling (CONSCAL)

Interpreting each dimension of a multidimensional configuration is conventionally done by comparing the obtained ordering of stimuli along that dimension to unidimensional scale values for those stimuli. These theoretically- or experimentally-derived scale values may also be used to constrain the configuration. This is important, since a configuration satisfies an interpretation whenever the ordering along a dimension exactly matches the accompanying scale values. Therefore, when the coordinates of the points are constrained, an interpretation is forced upon a configuration. In CONSCAL, the coordinates may be constrained in a specified order along one or more dimensions. All configurations satisfying these constraints are called feasible solutions.

One way to constrain a solution is by using an external penalty function. In this method, an iterative stress-minimizing procedure may initially generate a non-feasible configuration. This minimum-stress configuration, however, will be assessed a penalty so that a feasible configuration will tend to be generated in the next iteration.

CONSCAL uses an alternative approach. A non-feasible configuration may be generated during an iteration, but unlike the penalty function method, the coordinates of points in the configuration, X, are altered to form a feasible solution before the next iteration. The procedure can be implemented by modifying an iterative multidimensional scaling program, such as KYST or MDSCAL (Kruskal, 1964a), to use a two-step procedure: 1) a method such as the gradient method (Jacoby, Kowalik, & Pizzo, 1972) moves the points into a lower-stress configuration, and 2) points are moved to conform to the ordering constraints. The two steps alternate in each iteration until there is no improvement in stress, only alternation between two configurations - one produced by each half of the procedure.

There are many feasible configurations, so it is necessary to specify a function from a non-feasible coordinate matrix, X, to a feasible coordinate matrix, X'. We use a function mapping X into the feasible X' that minimizes the sums of the squared distances from X. This is equivalent to finding X'_{ik} coordinate values that minimize

$$\sum_{i=1}^{n}(X_{ik}-X'_{ik})^2$$

for all dimensions k. An algorithm developed by Kruskal (1964b, p. 128; see also van Eeden, 1957; Bartholomew, 1959; Miles, 1961) is used in step two to move the X'_{ik}'s into a specified order (one producing a feasible X').

Kruskal's monotone regression, as applied to interpoint distances, has two options for resolving ties, known as the primary and secondary approaches. In the primary approach, tied inter-item dissimilarities need not result in equal interpoint distances, while in the secondary approach, equal dissimilarities must result in equal interpoint distances. In CONSCAL, these two options are also available when specifying the monotone order of projection onto the axes: the primary approach is called weak dimensional monotonicity, and the secondary approach is called semi-strong dimensional monotonicity. In both, if the coordinates X_{ik} on a dimension k are constrained by scale value c_i, then the following is required:

$$\text{if } c_i > c_j, \text{ then } X_{ik} > X_{jk}.$$

Weak dimensional monotonicity makes no additional requirements (note that $c_i = c_j$ does not restrict the ranks of X_{ij} and X_{jk}). Semi-strong dimensional monotonicity makes the stricter requirement that:

$$\text{if } c_i = c_j, \text{ then } X_{ij} = X_{jk}.$$

Semi-strong dimensional monotonicity is usually used for scaling stimuli in a factorial experimental design, since all tied values of the independent variables used to create the factorial design are usually assumed to have the same coordinate values. However, when hypothesized psychological variables specify the order of projection onto the axes, weak dimensional monotonicity should usually be used. (For example, when two stimuli elicit category estimates of 6 on a 1-to-10 scale, there is little reason to believe that they are psychologically equivalent.)

The CONSCAL program also permits the testing of one nonlinear-constraint model in particular - a radex model. In this model (Levy & Guttman, 1975), the relative location of each point is constrained according to ordered distance from an origin and ordered angular displacement from an arbitrary vector starting at the origin. Since there are two relevant rank orders that locate each point in a polar coordinate two-dimensional subspace, the CONSCAL program uses the Kruskal monotone regression on both orders to obtain a feasible configuration.

An Application: Multidimensional Scaling of Ellipses

The following examples come from a study of the interactions among dimensions of stimulus variation in the perception of ellipses (for a theoretical discussion see Pachella, Somers, and Hardzinski, in press). We were interested in the ability of the following dimension pairs to characterize the judged similarities: physical area and physical eccentricity, judged area and judged eccentricity, or judged length of major and minor axes.

A factorial design with four equally spaced levels of area crossed with four equally spaced levels of eccentricity was employed in constructing the stimuli. The area of the largest ellipse was in a 3:1 ratio to the smallest, and the eccentricity of the most eccentric was in a 1.66:1 ratio to the least eccentric.[2] Black-on-white slides were made of these sixteen ellipses. All ellipses were presented with major axis horizontal.

Four subjects made dissimilarity judgments on a 10-point category scale for all possible pairs of ellipses. The entire set was presented three times, in a different random order each time, and the judgments were averaged for each subject. In another session, subjects made category estimates, on the same 1-10 scale, of the following properties of each ellipse: area, eccentricity, length of major axis, and length of minor axis. The order of these four tasks varied among subjects. Six judgments were made of the four properties for each of the 16 ellipses (384 judgments total), and the judgments were averaged for each subject in each task.

Unconstrained multidimensional scaling of the dissimilarity judgments showed

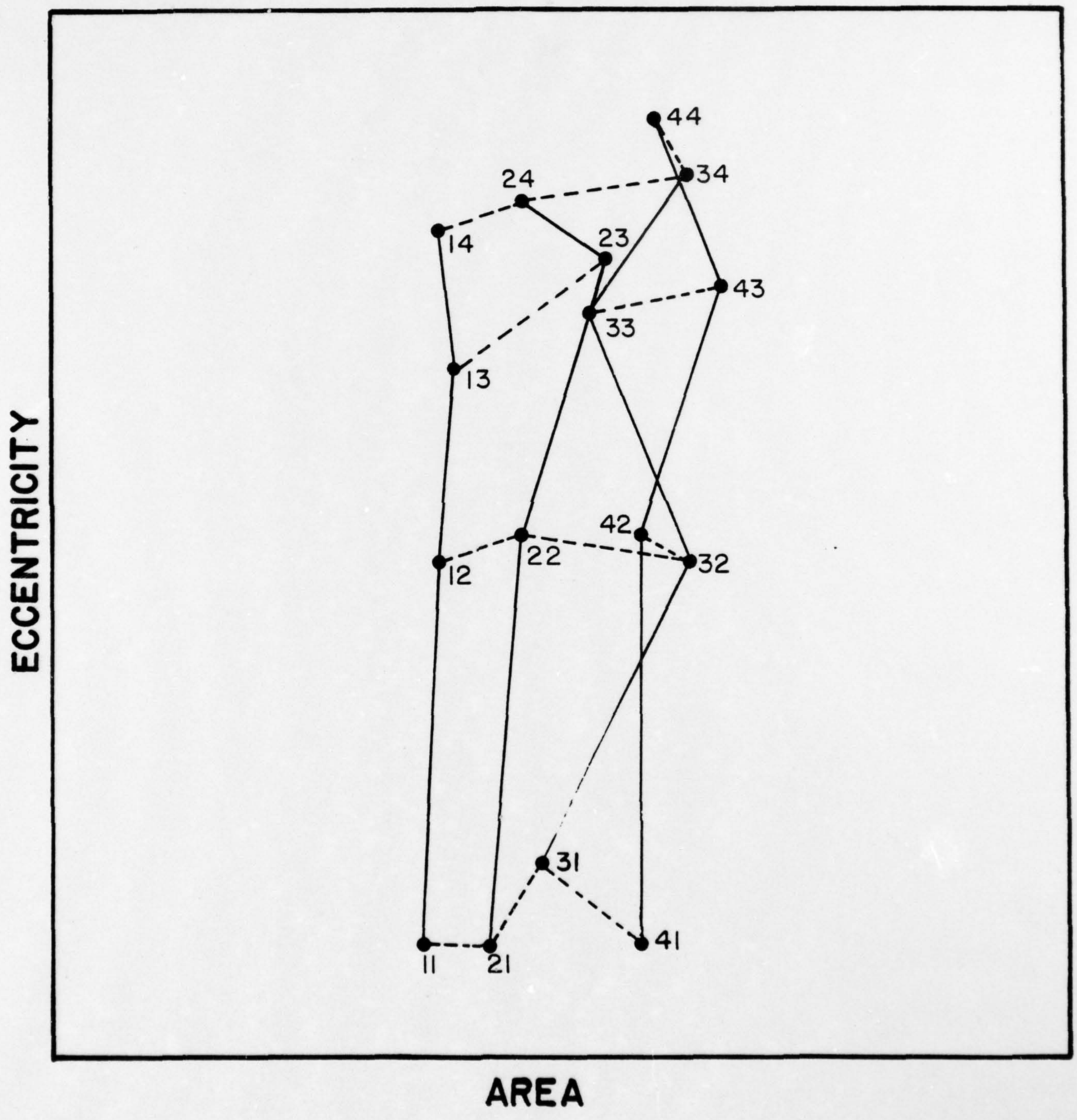

Figure 1. Dimensional interpretation of unconstrained MDS plot, subject RR.

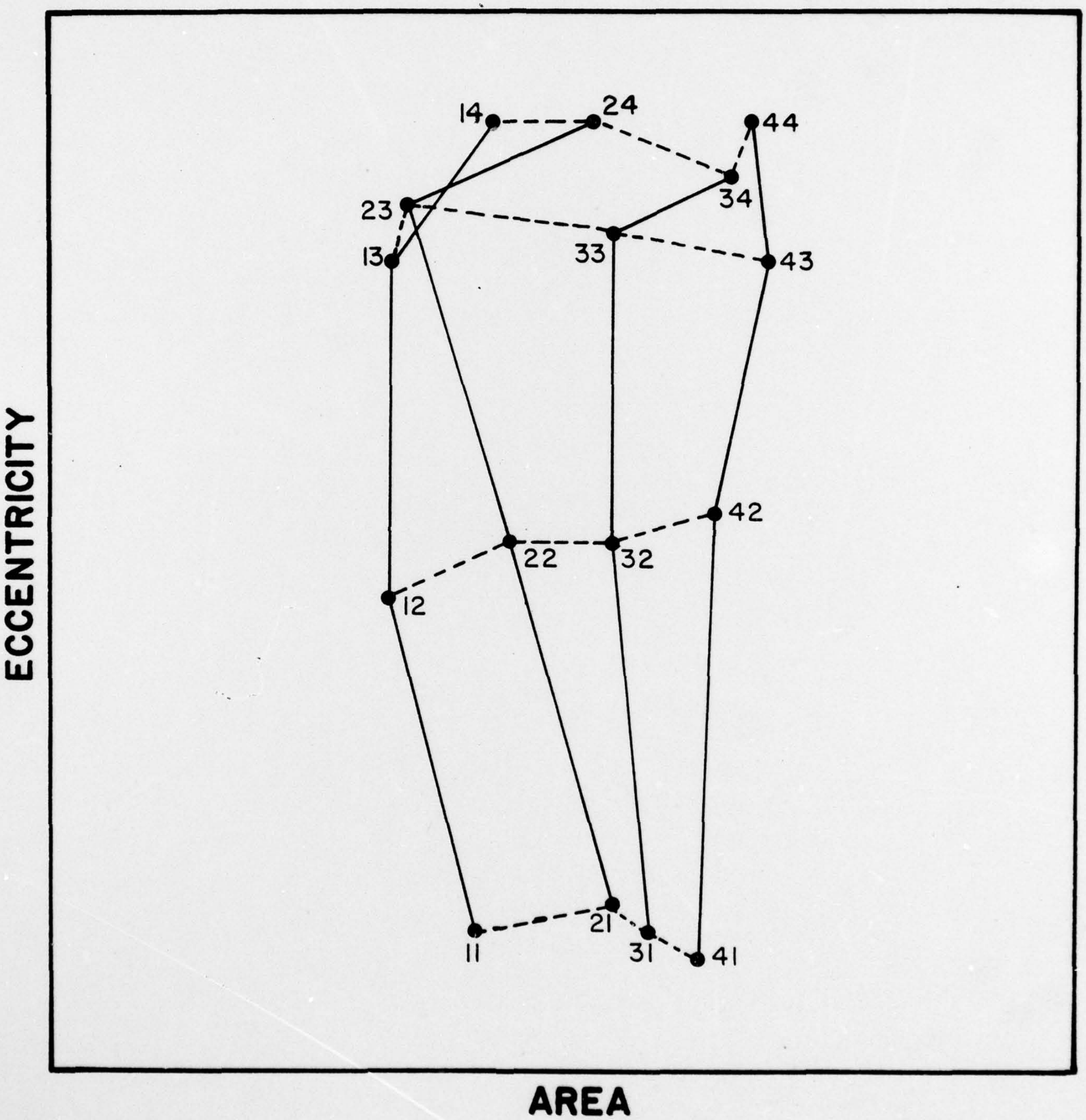

Figure 2. Deminsional interpretation of unconstrained MDS plot, subject JL.

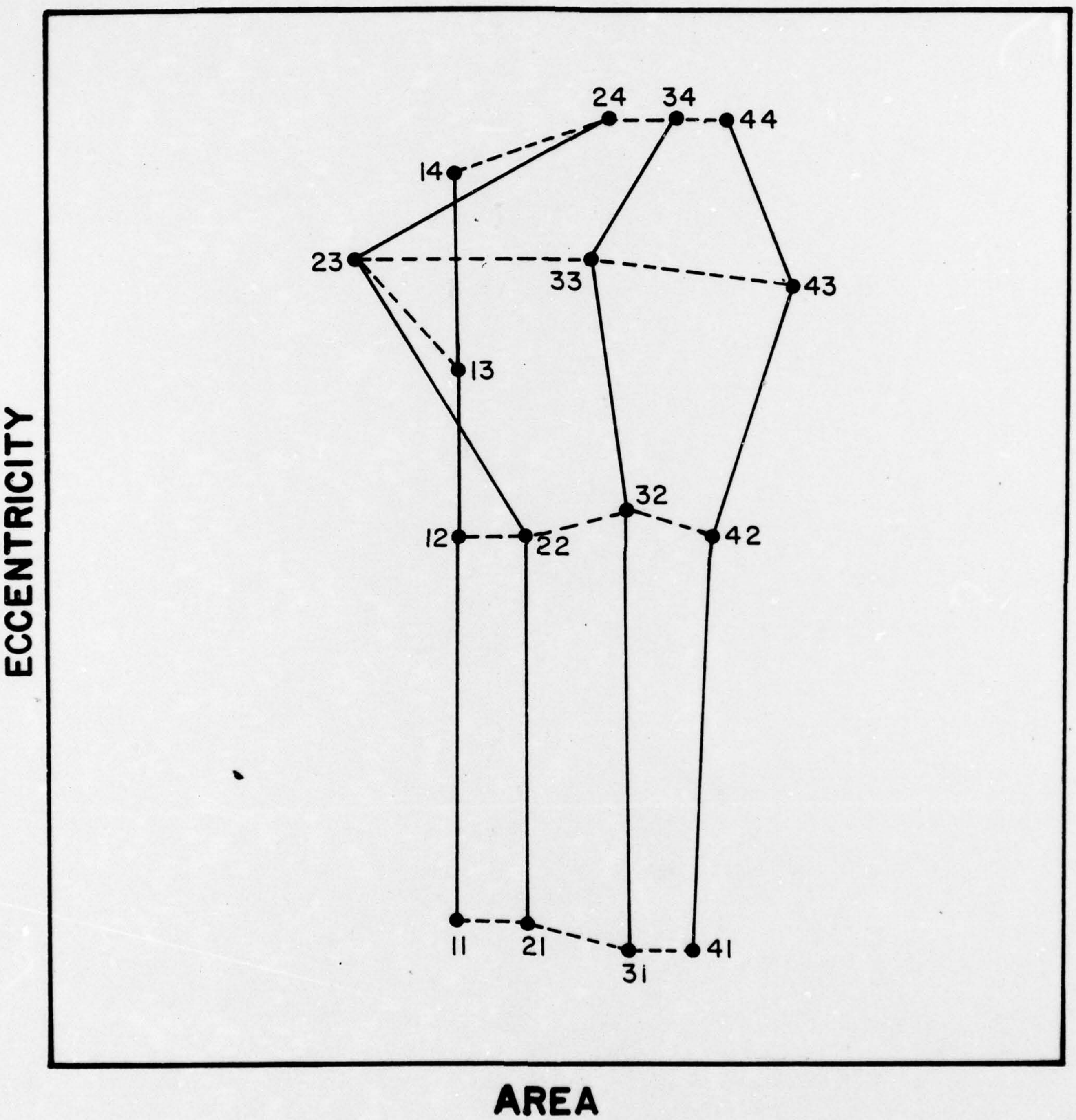

Figure 3. Dimensional interpretation of unconstrained MDS plot, subject TM.

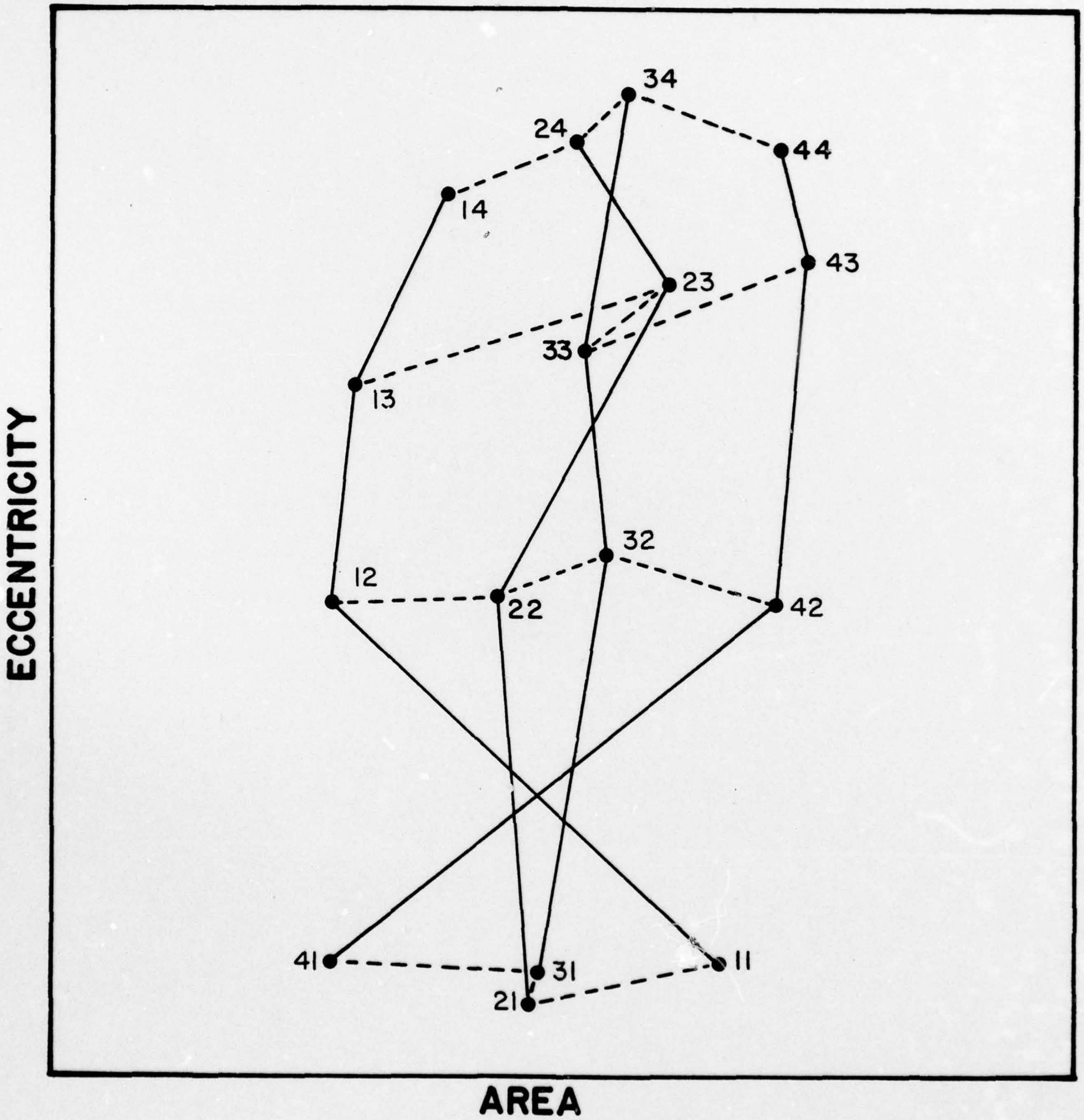

Figure 4. Dimensional interpretation of unconstrained MDS plot, subject DT.

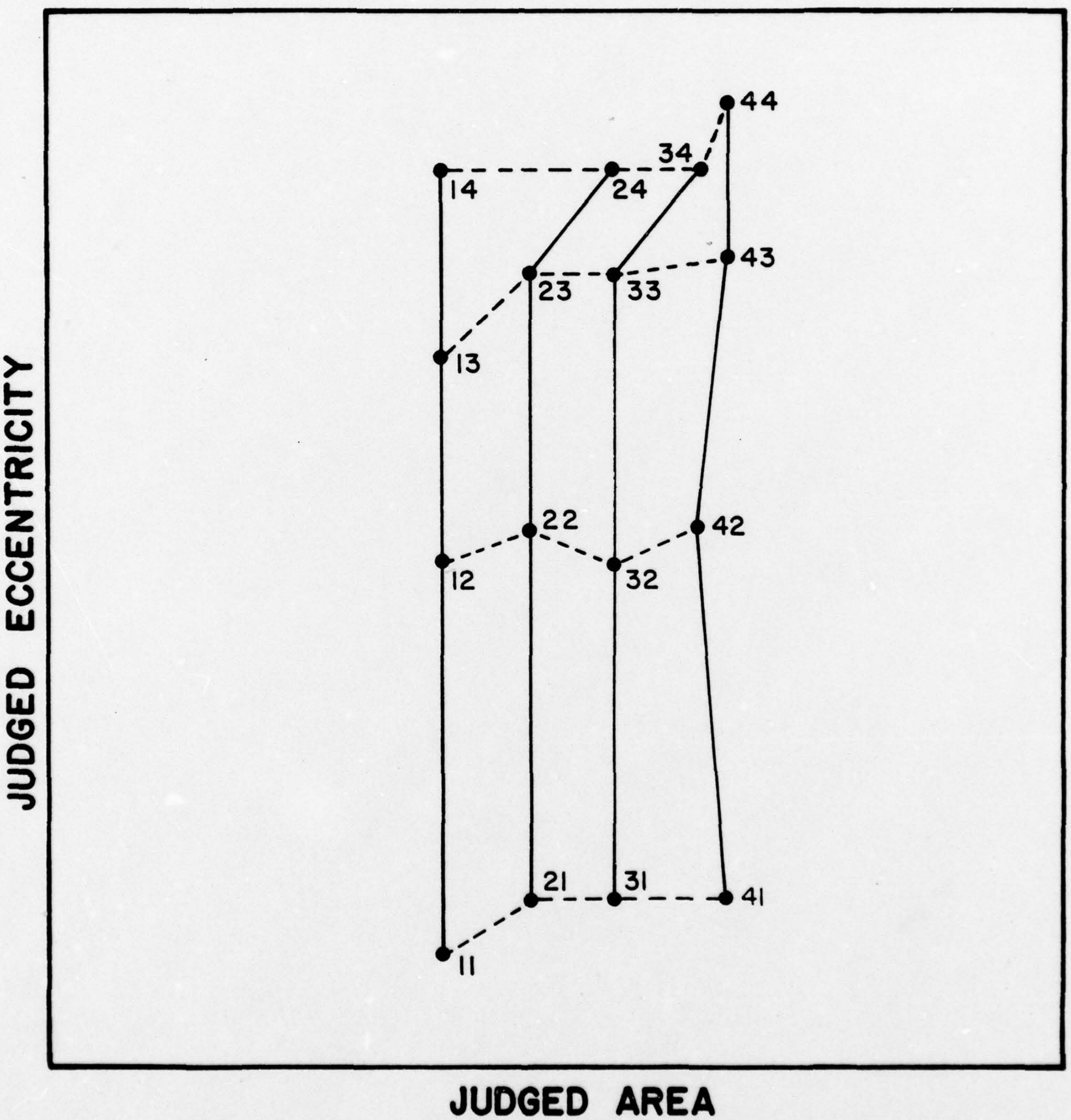

Figure 5. Confirmatory MDS plot; RR. Semi-strong monotonicity: dimensions of judged area and judged eccentricity.

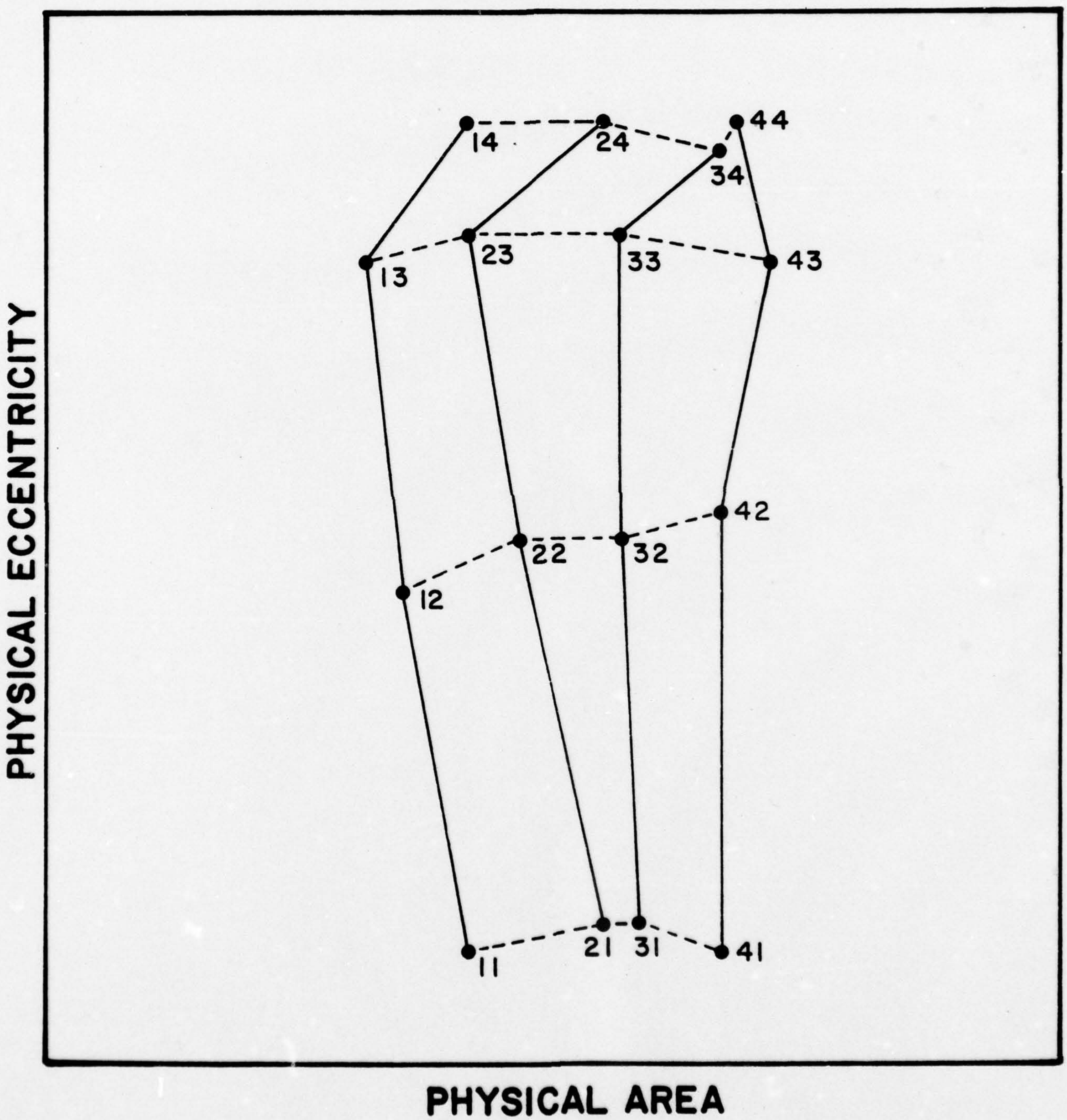

Figure 6. Confirmatory MDS plot; JL. Weak monotonicity: dimensions of physical area and physical eccentricity.

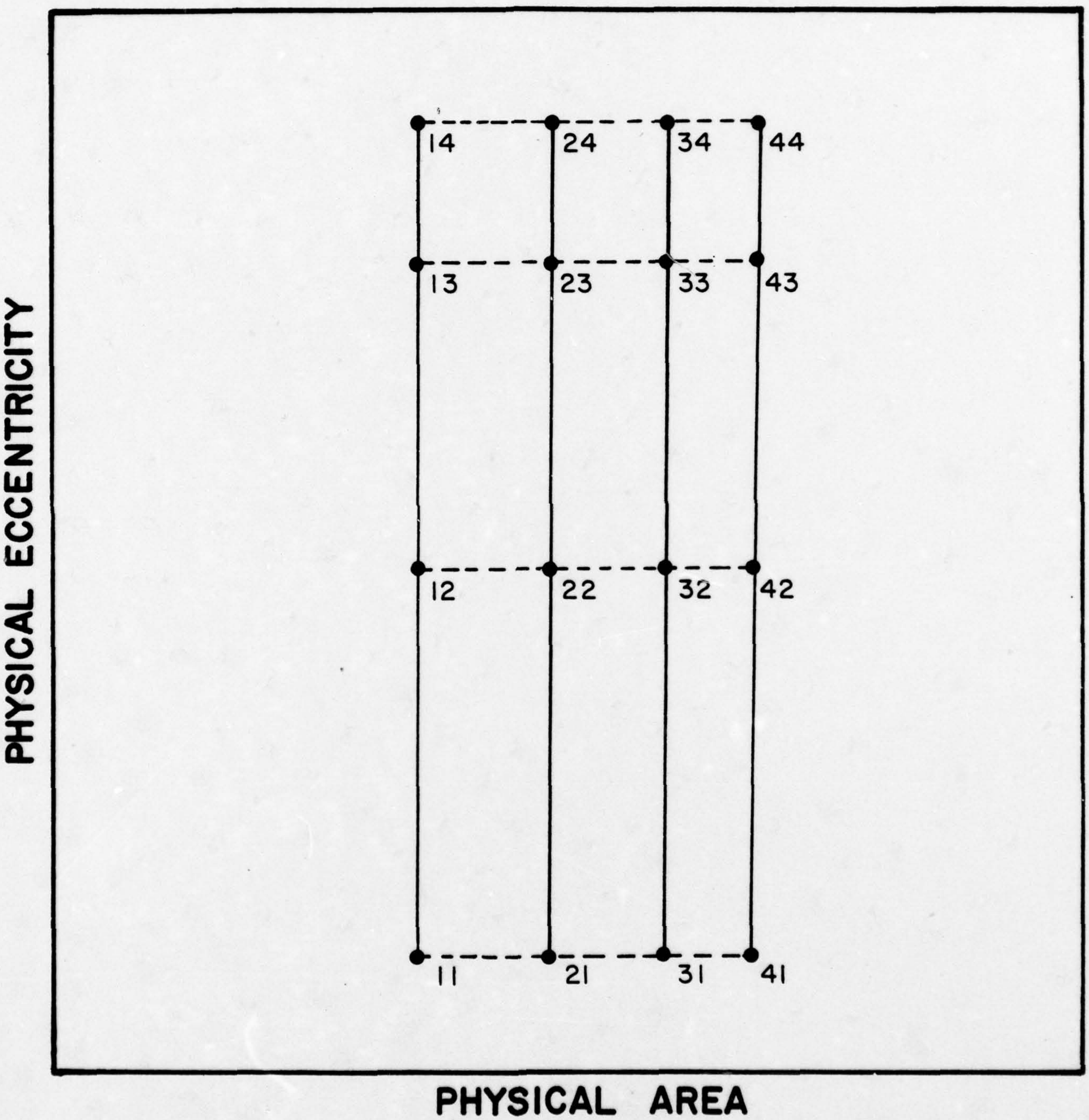

Figure 7. Confirmatory MDS plot; JL. Semi-strong monotonicity: dimensions of physical area and physical eccentricity.

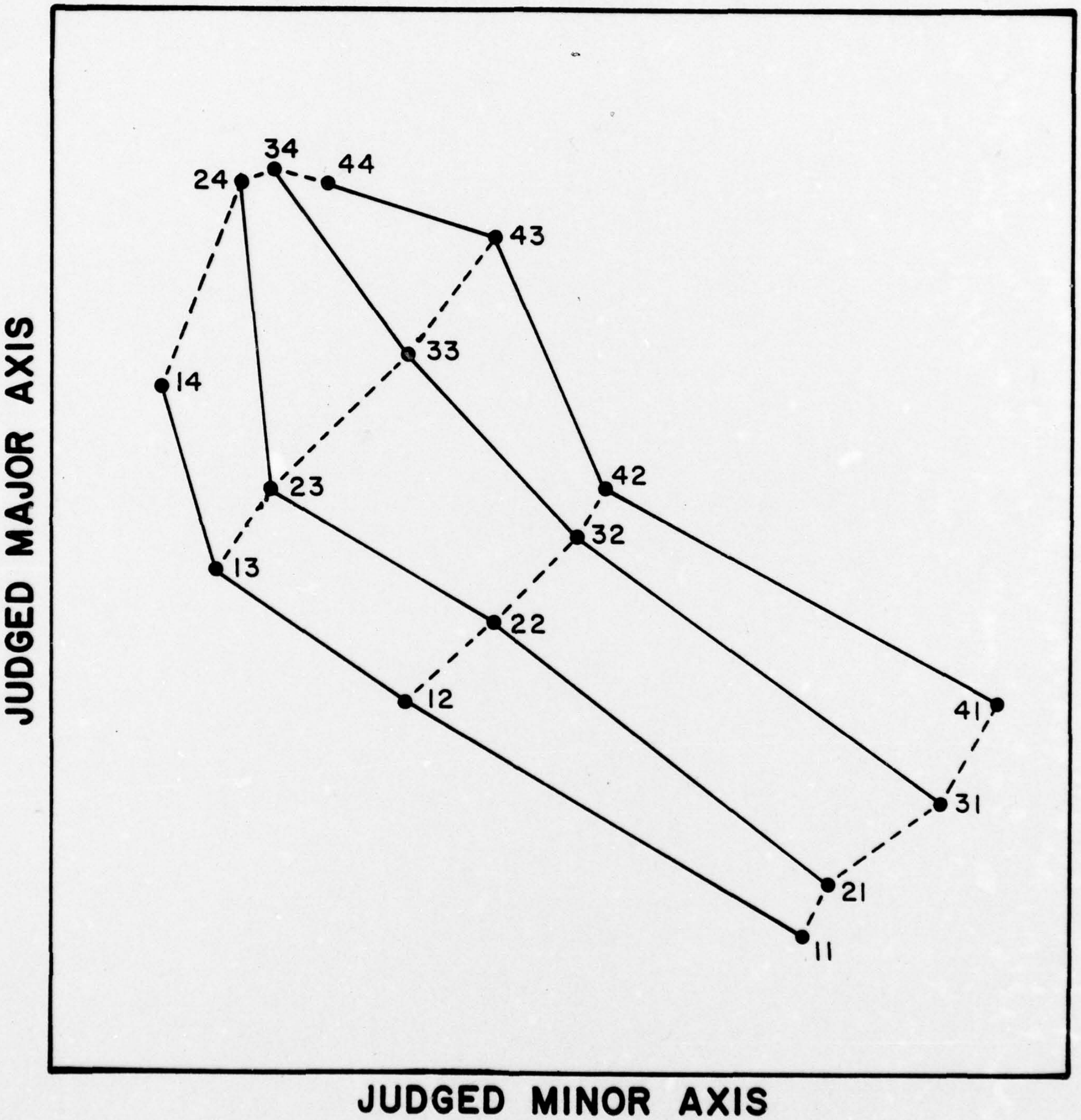

Figure 8. Confirmatory MDS plot; TM. Semi-strong monotonicity: dimensions of judged major and judged minor axes.

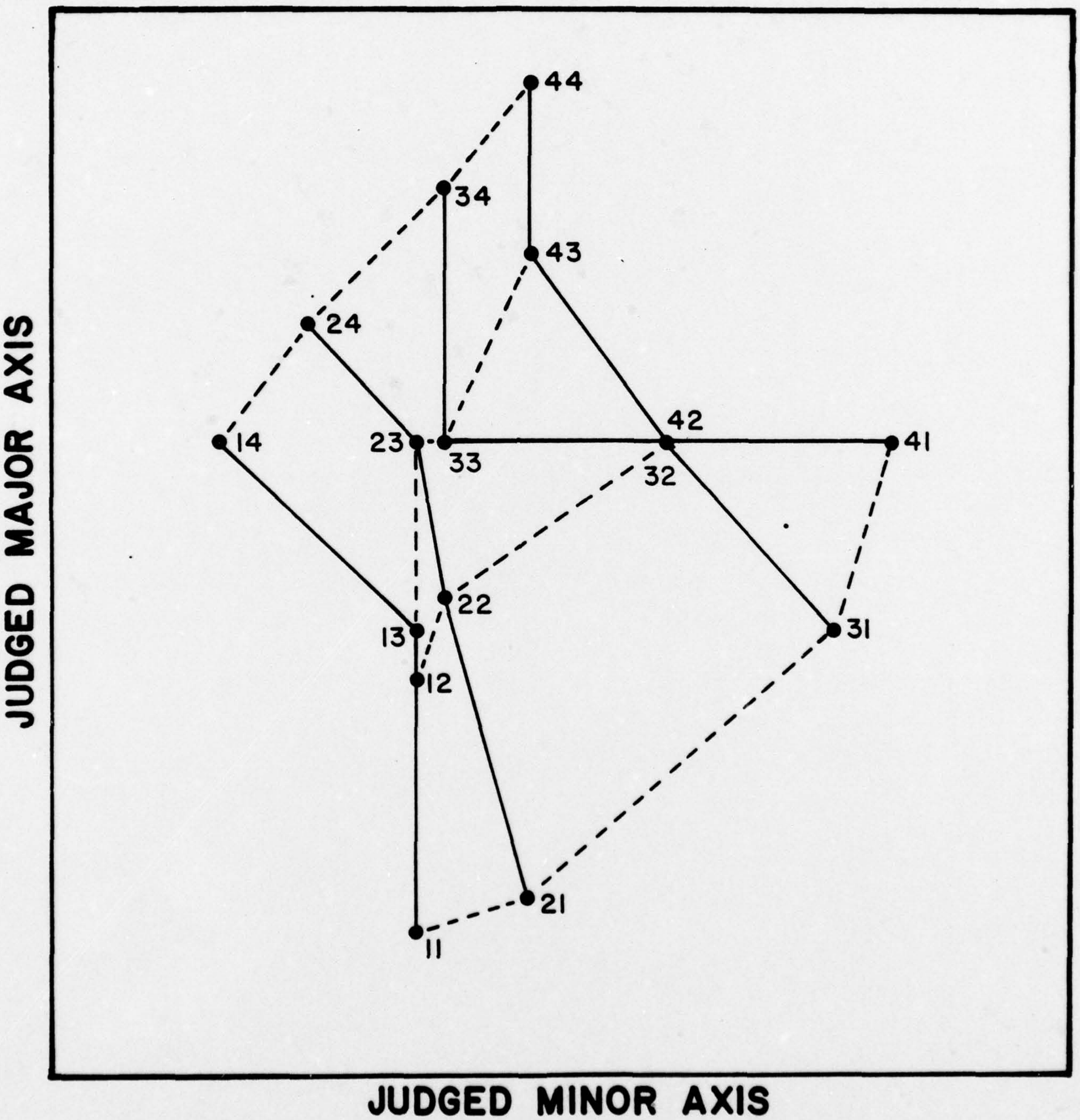

Figure 9. Confirmatory MDS plot; RR. Semi-strong monotonicity: dimensions of judged major and judged monor axes.

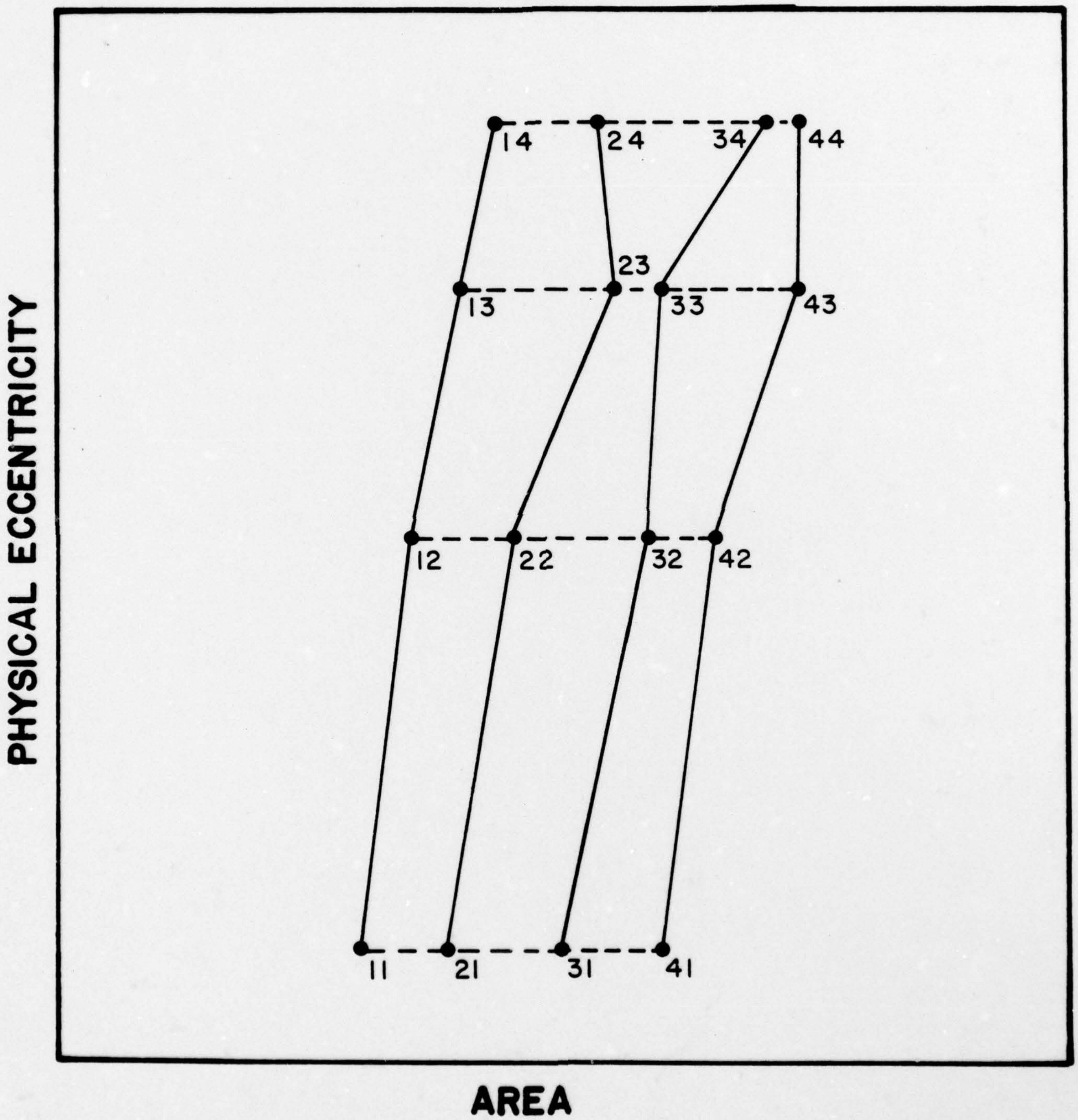

Figure 10. Confirmatory MDS plot; RR. Semi-strong monotonicity, with respect to dimension of physical eccentricity only. (Second dimension interpreted as area.)

Table 1

Stress Values for Configurations with and without Constraints, for Four Subjects

Confirmatory	DT	RR	JL	TM
A. Unconstrained	.131	.056	.087	.070
B. Weak Physical Area Physical Eccentricity	.136	.058	.089	.074
C. Semi-Strong Physical Area Physical Eccentricity	.155	.095	.109	.096
D. Weak Psychological Area Psychological Eccentricity	.163	.072	.093	.082
E. Semi-Strong Psychological Area Psychological Eccentricity	.174	.076	.100	.085
F. Weak Psychological Major Axis Psychological Minor Axis	.167	.186	.107	.089
G. Semi-Strong Psychological Major Axis Psychological Minor Axis	.174	.218	.113	.090
H. Semi-Strong Physical Eccentricity	.145	.081	.096	.079

generally good fits for all four of the subjects in two-dimensional Euclidean space. One configuration (subject DT) had a stress of .131 and the other subjects' configurations had stresses ranging from .056 to .087. We were reasonably confident that local minimum problems were being avoided because starts from either random or "hypothesized best fit" (area by eccentricity factorial design) configurations resulted in virtually identical stress values and configurations. For two subjects, a third dimension was added, but this made little difference in stress, and the extra dimension was uninterpretable.

In all four cases, clearly interpretable dimensions of area and eccentricity were present. There were a few minor deviations from the hypothesized orderings along the dimensions, as can be seen in Figures 1-4, and one major reversal of area levels within the smallest eccentricity level in the highest-stress configuration (DT, Figure 4). One question that cannot be answered using traditional stress-minimizing techniques is, how meaningful are such reversals?

Insert Figures 1-10 about here

Are they merely noise, or does the subject actually have some anomaly in his or her cognitive structure? One way we can try to answer this is to use a constrained multidimensional scaling analysis.

As can be seen in Table 1, constraining the configuration to fit the factorial design according to which the stimuli were constructed causes increases in stress from about .02-.04 for each subject, indicating that this model does

Insert Table 1 about here

reasonably well for all four subjects. In fact, the configuration with the major reversal (DT, Figure 4) shows the second-lowest increase in stress--only .026. Even without a statistical analysis, this would seem to indicate that even though her deviations from the model appeared to be more systematic than those of the other subjects, they seem to be no more important.

Comparing judged area and judged eccentricity with physical area and physical eccentricity produced little difference in either stress values (see Table 1) or configurations (see Figures 5 and 6). One would naturally expect the factorial design, with strong monotonicity (see Figure 7), to produce higher stress than any of the other models because of the large number of ties which must be satisfied. These results indicate two things: (1) subjects' scaling of area and eccentricity are reasonably veridical (which is not particularly surprising), and (2) models based upon dimensional combinations of physical versus judged area and eccentricity are for the most part interchangeable, with preference perhaps going for the factorial design model because of its greater simplicity.

Comparing judged area-eccentricity to judged major axis-minor axis models proved more interesting. For three of the subjects, the area-eccentricity and major axis-minor axis models were approximately equivalent in terms of stress, and produced highly similar configurations (compare Figures 3 and 8, for example). However, for one subject, there was a dramatic difference in stress between area-eccentricity and major axis-minor axis configurations. For RR, at least, even though the two models are physically equivalent, they are not psychologically equivalent (compare Figures 5 and 9). This comparison also shows that there can be dramatic individual differences between subjects regarding the applicability of certain models even though the configurations may appear quite similar.

Using confirmatory multidimensional scaling, it is also possible to constrain only a subset of the dimensions. This might be especially helpful if one has strong hypotheses only about some of the dimensions a subject is expected to use, but not about all of them. For example, in Figure 10, eccentricity, but not area, is constrained.

Discussion

There is no universally accepted procedure for statistically evaluating the stress value of a configuration produced by an unconstrained multidimensional scaling algorithm. The problem of evaluating the difference in stress between constrained and unconstrained configurations is even more complicated. Young (1970) has suggested a degrees-of-freedom approach. Using Young's terminology, in the unconstrained multidimensional scaling of N points in a space of d dimensions, there are $N(N-1)/2$ degrees of freedom of the dissimilarities and $d(N-1)-[d(d-1)/2]$ degrees of freedom of the coordinates. Young demonstrates that in general, the stress increases with either increases in the degrees of freedom of the dissimilarities (number of points) or decreases in the number of degrees of freedom of the coordinates.

In certain cases, such as that of semi-strong dimensional monotonicity with a factorial design, the degrees of freedom of the coordinates are drastically decreased. For instance, in a four-by-four factorial experimental design, there are 120, or $16(16-1)/2$, degrees of freedom of the dissimilarities. In an unconstrained multidimensional scaling of the points in two dimensions there are 29, or $2(16-1)-[2(2-1)/2]$, degrees of freedom of the coordinates. By contrast, a constrained multidimensional scaling in a two-dimensional four-by-four design using semi-strong dimensional monotonicity has only 5, or $2(4-1)-[2(2-1)/2]$, degrees of freedom of the coordinates. Extending Young's analysis, it might be expected that the stress in the constrained analysis should be much higher than that of the unconstrained solution. However, in our analysis of three of the four subjects we found no large differences in stress when comparing unconstrained and constrained analyses. This seems to imply that the factorial design is the best representation of the data.

There are several reasons why the above approach is inadequate. One problem is that the ordinal-scale assumption of the dissimilarities does not lend itself to a degrees-of-freedom analysis. Another is that we lack prior knowledge of the number of parameters needed to characterize a constrained solution. It is also unclear how weak dimensional monotonicity and nonfactorial designs could be interpreted in light of a degrees-of-freedom analysis. A further problem is that there are no adequate statistics for evaluating stress for constrained, or unconstrained, multidimensional scaling outputs. This, of course, is a problem for multidimensional scaling in general.

Such difficulties notwithstanding, constrained multidimensional scaling offers unique advantages in its new approach to interpretation. Some such advantages can be seen by comparing and contrasting other interpretation methods with constrained scaling. Of particular interest in this context are other methods for fixing vectors through the space, such as principal components analyses, regression methods, and some methods for drawing cross-configuration comparisons. These interpretation methods fix vectors through the space with an accompanying goodness-of-fit measure after a multidimensional scaling algorithm fixes points in a space and computes the stress. (For a broader discussion of alternative interpretation methods, see Noma and Johnson, 1977).

An example of a method for comparing configurations is PINDIS (Lingoes & Borg, 1978), which fixes axes through a space by combining configurations across subjects. The PINDIS method optimizes two goodness-of-fit criteria - one within each individually scaled configuration (stress), and another across configurations. Such a method is potentially susceptible to tradeoffs between these two criteria. The validity of approaches in which one or more configurations are compared may also be questioned because there might be slight modifications of each configuration that would produce vastly different goodness-of-fit measures across configurations, and change the group space.

Both principal components analysis (see Napior, 1972) and regression of independent variables onto the point coordinates (see Chipman and Carey, 1975) locate vectors in a fixed space. In both, there are two goodness-of-fit measures optimized by the scaling methods. The multidimensional scaling algorithm minimizes stress, while the principal components and regression methods maximize explained variance. There may be a tradeoff between these two optimization criteria. A configuration with higher than minimal stress may give rise to a better-fitting vector through the space. Alternatively, using a lower-stress configuration in a higher dimensionality might change the fit of the vector. CONSCAL resolves these tradeoff problems by perfectly fitting the vector through space before constructing the configuration.

One other method for testing an interpretation of a configuration may be the Krantz and Tversky (1975) axiomatic tests incorporating an error theory. Such tests set limits on the number of axiom violations acceptable, given a model of random errors. Constrained scaling may also have an advantage over such axiomatic tests in that estimates can be made of the "importance" of violations of the axioms. In other words, some violations of the necessary axioms may be of little psychological interest, since they are an artifact of a particular experimental paradigm. If a subject, for instance, rank orders the inter-stimulus dissimilarities, he may use an arbitrary rule to break ties. However, a measurement theoretic analysis of such data may result in interpreting this bias as an important psychological effect. Scaling these data with a constrained multidimensional scaling shows these anomalies to be unimportant, as they contribute little to the stress.

Using constrained scaling, models of the psychological attributes determining a set of responses may be developed and tested by first scaling the dissimilarity measures using an unconstrained multidimensional scaling method. From this output configuration, and from theoretical arguments, possible interpretations can then be formulated. By applying constrained multidimensional scaling, the relative validity of each interpretation may be assayed.

Despite its shortcomings, CONSCAL offers a different approach to multidimensional scaling by emphasizing the testing and comparing of interpretations. By permitting a hypothesis-testing approach, CONSCAL may provide strong support for a particular interpretation of spatially scaled data since it is not vulnerable to stress-interpretability tradeoff problems. In contrast, conventional multidimensional scaling approaches are exploratory and provide weaker support for specific interpretations. In summary, CONSCAL determines how the goodness-of-fit measure is affected when a given model is satisfied, rather than determining how closely the scaled output resembles a hypothesized space.

Footnotes

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[2]area = $\Pi \cdot \text{major} \cdot \text{minor}$

$$\text{eccentricity} = \sqrt{\;-\left(\frac{\text{minor}}{\text{major}}\right)^2}$$

The area levels were (in arbitrary units): .3, .5, .7, .9.

The eccentricity levels were: .600, .940, .986, .995.

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