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Multidimensional scaling analyses of two construction-related tasks

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Abstract Representations involved in two construction-related tasks were analyzed by multidimensional scaling (MDS), a statistical technique that allows the dimensions of internal representations to be derived from empirically obtained judgment data. The tasks involved judgments of how similar two objects were and how well they fitted together; these judgments are related to copying and assembly abilities that are impaired in constructional apraxia. Analyses of numerical subjective ratings and response times for these judgments showed that within the same set of geometric objects, different shape-related properties were emphasized under different task conditions. The similarity judgment depended most on a representational dimension related to enclosure of space, while the fit judgment depended to a greater extent on a dimension related to the objects' symmetry properties. This pattern of results was found in both subjective ratings and response times, as analyzed by MDS and by confirmatory classical statistics. The findings suggest that construction-related tasks depend on representations that are context-dependent, and that MDS may be useful in a variety of settings as an intermediate-level tool for analyzing representations related to context-specific abilities.

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Introduction

In everyday interactions with objects in our environment, our success at generating appropriate actions in different functional contexts depends implicitly on abilities to analyze relationships among objects and to judge their suitability for particular purposes. A primary problem, if we wish to better understand these abilities, is to determine what representations are involved in such judgments, and how they can be fine-tuned in the contexts of specific behavioral goals.

The qualities of such representations may be difficult to determine from introspection or first principles, but they can be derived empirically from human performance of relational judgments using multidimensional scaling (MDS), a statistical technique for analyzing the structure of relational data. MDS translates the measured relationships between pairs of objects into a best-fit geometric configuration of points in space, such that closely related object pairs are reflected by points that are close together, and dissimilar objects correspond to points that are far apart (Kruskal and Wish 1978; Davison 1983). The dimensions along which the configuration is organized reflect the dimensions of internal representations as they are used by cognitive processes (Beals et al. 1968; Baird and Noma 1978; Shepard 1980). Parameters of a cognitive model can thereby be derived in a data-driven fashion, without depending on prior knowledge of hypothetical variables of interest. MDS has been used for psychophysical analysis and many other mathematically similar problems, and may be applied to distance-like quantities, or *proximities*, as well as other types of data from which proximities can be obtained (Kruskal and Wish 1978).

The present work uses MDS to characterize the representations of a set of simple objects in the context of two different relational judgments. Presented with pairs of visual objects picked from a set of geometric fragments of a square (Fig. 1), subjects were asked (1) to judge the similarity of the objects, using either a numerical subjective rating scale or a timed same-or-different response, or (2) to judge how well, or whether, the two objects fitted together to form a complete square.

These tasks, referred to as the *similarity* task and the *fit* task, respectively, were designed to parallel two construction-related abilities that are impaired in a form of apraxia. Patients with apraxia have difficulty generating appropriate actions in specific functional contexts, even though they may exhibit no deficits in movement per se, or in more general capacities of comprehension or attention (Wilson 1909; Liepmann 1920/1988; Geschwind 1975). Constructional apraxics are typically impaired in their abilities to copy a visually presented object or to assemble a whole object from component parts (Benton 1967; Gainotti 1985). The former ability would be expected to depend on judgments of similarity, whereas the latter would depend on judgments of fit. We were therefore interested in identifying the dimensions of representations involved in these judgments and, by comparing the two, in determining the extent to which those representations were context-specific.

Materials and methods

Behavioral methods

Subjects

Three men and three women, 20–38 years of age, were paid U.S. $ 10/h to serve as subjects in this experiment. One subject wrote with his left hand; the other five were right-handed. All subjects were in good health and were naive as to the purpose of the experiment. Informed consent was obtained from all subjects based on the protocol approved by the Institutional Review Board.

Stimuli

Pairs of visual objects, from the set of 25 geometric fragments of a square shown in Fig. 1, were presented on a large-format monitor under computer control. The white-on-black objects, which ranged in size from approximately 1.25° to 2.5° across, were presented approximately 9° apart, appearing at random diametric positions on an imaginary circle (e.g., 10 o'clock and 4 o'clock). In blocks of trials requiring timed "yes-no" responses, the objects were flashed for 50 ms and followed by a 400-ms white mask. On trials in which numeric subjective ratings were recorded, the objects remained on screen until a response was collected.

Each block of trials consisted of a complete presentation of all 325 possible pairs of the 25 objects. Typically, this took about 15 min, including 1-min rest periods approximately 5 and 10 min into the block.

Tasks

Subjects used the computer keyboard to initiate trials and to make "yes," "no" (J and K keys, respectively), or numeric responses (1 to 6 on the numeric keypad, with larger numbers corresponding to higher ratings of similarity or fit). They were instructed, in separate blocks, to respond according to the similarity or fit of the presented objects. The diagram in Fig. 2 was used as an aid to explain the two tasks. Objects were considered to be the same only if they were identical in both shape and orientation. Likewise, they were considered to exactly fit only if the objects could, by translational motions alone, be put together to form a square. Other than the specific examples illustrating exact similarity and fit, subjects were offered no explicit criteria for judging similarity or fit in relative degrees.

Subjects completed four blocks of trials representing each of the task and response conditions (subjective rating of similarity, similarity response time, subjective rating of fit, and fit response time) in each of four sessions conducted on separate days, for a total of 16 blocks of data collected in a digram-balanced Latin square design (Wagenaar 1969). Subjects performed a minimum of 20 practice trials before each block to accustom themselves to changes in conditions.

Analytical methods

Response data from these tasks were analyzed by a combination of classical statistics and MDS. Regressions were used to determine average properties of the raw responses, including the relationship between subjective ratings and response times. MDS was then used to derive dimensions of representations used in each task; these analyses were especially useful for qualitative characterization and comparisons between tasks. Finally, analyses of variance were applied to the raw response data, to assess the significance of effects along dimensions identified by MDS.

General overview of MDS

From a matrix of judgment data reflecting cognitive or perceptual relationships, MDS can be used to derive a corresponding configuration of points in space, defined by geometric relationships of distance. The input data are expressed as proximities: relatedness of each pair of objects is represented by smaller numbers for object pairs that are more alike, larger numbers for pairs that are more different. It is to these proximities that the configuration of points is fit, in a manner that maximizes the correspondence between derived interpoint distances and the given proximities. The problem is analogous to being given the table of intercity distances from a highway map (a matrix of proximities) and reconstructing from that the relative locations of the cities themselves (the configuration space).

Two quantities need to be specified in a mathematical model distance and goodness of fit – before the problem can be solved. Distance is most often measured in Euclidean terms, based on the sum of squared differences between coordinates in each dimension. In weighted MDS models such as Carroll and Chang's (1970) INDSCAL model, a weighted sum of squares is substituted, where the relative weights of each dimension for each subject can be thought of as representing individual differences in perspective on a common configuration space (just as one's angle of view affects the perceived relative dimensions of an ordinary object in space; Arabie et al. 1987).

Goodness of fit is treated differently depending on what types of quantitative relationships among proximities are regarded as meaningful. Nonmetric MDS may be applied to measures in which ordinal relationships are well defined, but other arithmetic relationships are not; for example, a similarity rating of "6" is interpreted as indicating greater similarity than a rating of "3", but the proposition that one object pair is "twice as similar" as another is not considered meaningful. Nonmetric analyses typically minimize a cost function called *stress* (Kruskal 1964), a sum of squares measure of departure from monotonicity between ranked proximities from the input matrix and corresponding distances in the configuration space.

Proximity measures

Matrices of proximities, representing the relatedness of each object pair under each task and response condition, were obtained from the responses of each subject according to the following rules:

Let $s_{sr(\mathrm{AB})}$, $s_{rt(\mathrm{AB})}$, $f_{sr(\mathrm{AB})}$, and $f_{rt(\mathrm{AB})}$ denote average subjective ratings and response times (subscripts *sr* and *rt*) collected during the similarity and fit tasks (*s* and *f*) during pairwise presentations of objects A and B; $\delta_{(\mathrm{AB})}$, the proximity of objects A and B; and ~A, the complement of A, such that A and ~A fit together perfectly to form a square (e.g., objects 1 and 19 in Fig. 1).

From subjective ratings of similarity and similarity response times, which were largest for object pairs judged to be most similar (see "Results"), proximities were obtained by taking additive and multiplicative inverses, respectively:

$$\delta_{(\mathrm{AB})}(s_{sr})=9-s_{sr(\mathrm{AB})} \tag{1}$$

$$\delta_{(\mathrm{AB})}(s_{rt})=\frac{1}{s_{rt(\mathrm{AB})}} \tag{2}$$

The constants 1 and 9 kept all proximities in the positive range; since subsequent MDS analyses were nonmetric, the choice of constants was otherwise arbitrary. Object pairs AB spanned all 325 pairs of the 25 objects; Eqs. 1 and 2 thereby each defined a 25-by-25 symmetric matrix.

From the fit task, proximities were obtained according to the logic that, if two objects are alike, they should fit well with one another's complements; thus, proximities were estimated by:

$$s_{(\mathrm{AB})}(f)=\mathrm{average}(f_{(\sim\mathrm{AB})}, f_{(\mathrm{A}\sim\mathrm{B})}) \tag{3}$$

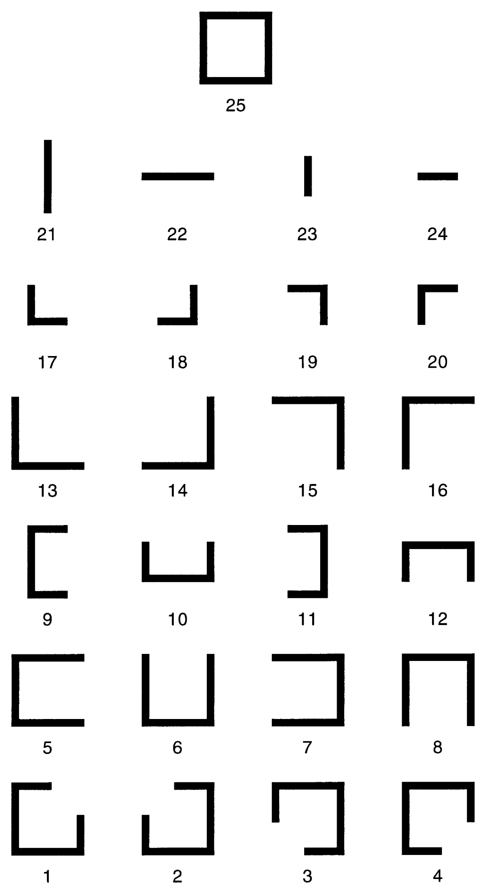


Fig. 1 Set of 25 geometric fragments of a square used as objects in pairwise visual presentations

following which, Eqs. 1 and 2 could be applied as before:

$$\delta_{(\mathrm{AB})}(f)=\delta_{(\mathrm{AB})}(s(f)) \tag{4}$$

For example, the proximity of objects 15 and 19 (Fig. 1) in the representation used by the fit task was estimated according to judgments of fit between objects 15 and 1, and objects 19 and 13. Three objects (objects 23, 24, and 25) did not have complements within the object set and therefore could not be included in analyses requiring this transformation.

If a fixed, context-independent representation were used by both the fit and similarity tasks, then the judgment, "do A and B fit together?" could be thought of as being no more and no less than the judgment, "is A the same as the complement of B?" (or vice versa), and proximities derived from both tasks would be expected to be the same. Alternatively, systematic differences between proximities derived from the two tasks would indicate differences in their underlying representations or fine-tuning according to behavioral context.

Multidimensional scaling

Configurations of points were fit to these proximity matrices by weighted nonmetric MDS, as implemented by the ALSCAL procedure (Takane et al. 1977) of SPSS (/MODEL=INDSCAL/LEVEL=ORDINAL). Configuration spaces for single subjects derived according to unweighted ALSCAL analyses were also examined. Note that in the analyses of "yes-no" response times, proximities corresponding to correct "yes" responses in either task fell along matrix diagonals ($\delta_{(\mathrm{AA})}$) which are ignored by the algorithm. Configurations derived from response times were therefore based entirely on variation among "no" responses; they do not represent variation due to responses that were motorically different.

Significance testing

The interpretations of MDS configuration spaces, which are of a qualitative nature, were compared with analogous classical statistics that measured the effects of each of three relational dimensions identified by MDS on response measures in the two tasks. The significance of these effects was tested by repeated measures analyses of variance, as implemented by the GLM procedure of SAS (using the REPEATED statement). As with the MDS analyses, subjective ratings and response times from correct "no" trials were analyzed. The GLM procedure was also used for regression analyses of raw responses.

Results

General response characteristics

Pairwise response measures were collected from six subjects, each of whom performed 1300 trials of each task (similarity or fit) under each response condition (numerical subjective rating or timed "yes-no" response). Overall performance on "yes-no" response time trials was 96% correct in both the similarity and the fit tasks.

The response times measured in "yes-no" trials were systematically related to subjective ratings of the same object pairs. Response times were shortest for pairs that were rated to be least similar or poorest fitting, and lengthened with increasing subjective ratings. Data for all 325 object pairs were fit by a regression model of the form:

$$RT=b_0+b_1\ (\text{subjective rating})+b_2\ (\text{yes-no})+\varepsilon \tag{5}$$

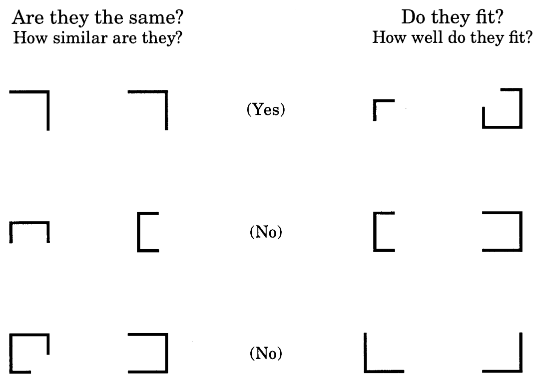


Fig. 2 Chart of examples used for instruction of subjects on the similarity and fit tasks

with slopes of b_1=27.2±3.4 ms per subjective rating point and b_2=164±16 ms for the “yes-no” effect in the similarity task (intercept b_0=413±9 ms; model $F_{[2,\ 3221]}$= 302, P<0.0002; R^2=0.65), and b_1=49.3±6.2 ms per subjective rating point and b_2=461±36 for the “yes-no” effect in the fit task (intercept b_0=437±14 ms; model $F_{[2,\ 3221]}$=300, P<0.0002; R^2=0.65).

Multidimensional scaling analysis

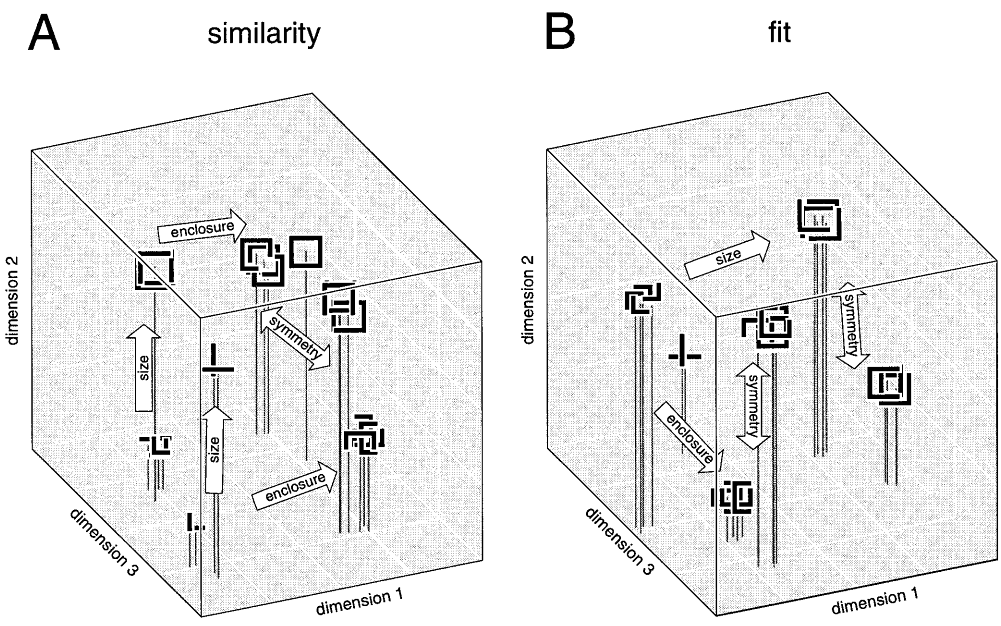
The pairwise data from each subject performing each task were then transformed into proximity matrices, which were calculated such that if the similarity and fit tasks depended on an identical, context-independent object representation, the relative proximities computed for the two tasks would be expected to be the same. These proximity matrices were then fit by the ALSCAL algorithm to a weighted nonmetric model (INDSCAL).

Configuration spaces were examined in one to four dimensions. As is generally the case, stress of the configurations decreased with increasing numbers of model dimensions. Configurations of up to three dimensions revealed structure in the data that was increasingly interpretable in terms of qualitative relationships among the objects. Additional dimensions in four-dimensional configurations, in cases where they were interpretable, appeared to relate to distinctions that applied only to small subsets of the objects.

Figure 3A shows the configuration space in three dimensions derived from subjective ratings of similarity. Each of the 25 oriented objects used in the pairwise visual presentations is represented by a likeness of the object plotted in three-dimensional space. Objects of identical shape but different orientation are clustered together, indicating that orientation was not among the factors accounting for greatest variance in subjective ratings and, likewise, that relationships in the configuration space among objects of the same shape were essentially replicated across orientations.

The dimensions accounting for greatest variance in these data, represented by the axes of the three-dimensional configuration space, correspond to three shape-related properties, summarized in Fig. 4. Dimension 1, corresponding to the largest amount of variance in the given proximities, separates the simplest bar- and corner-like objects from the bracket- and box-like objects that might be thought of as enclosing some space; hence, we shall refer to this as a dimension of *enclosure*. Dimension 2 appears to correspond to object *size*, with the smaller bars, corners, and brackets appearing in the lower half of the configuration space, and the larger corresponding shapes appearing directly above along the dimension 2 axis. Finally, dimension 3 may be related to properties of object symmetry. The bar- and bracket-like objects in the front of the configuration space are characterized by horizontal or vertical axes of symmetry, while the shapes in the back of the space have diagonal axes of symmetry; the square, at an intermediate depth, has symmetry of

Fig. 3 MDS group configuration spaces derived from subjective ratings of A similarity and B fit. The geometric arrangements of objects in the configuration spaces reflect the dimensions of internal representations used in the two tasks



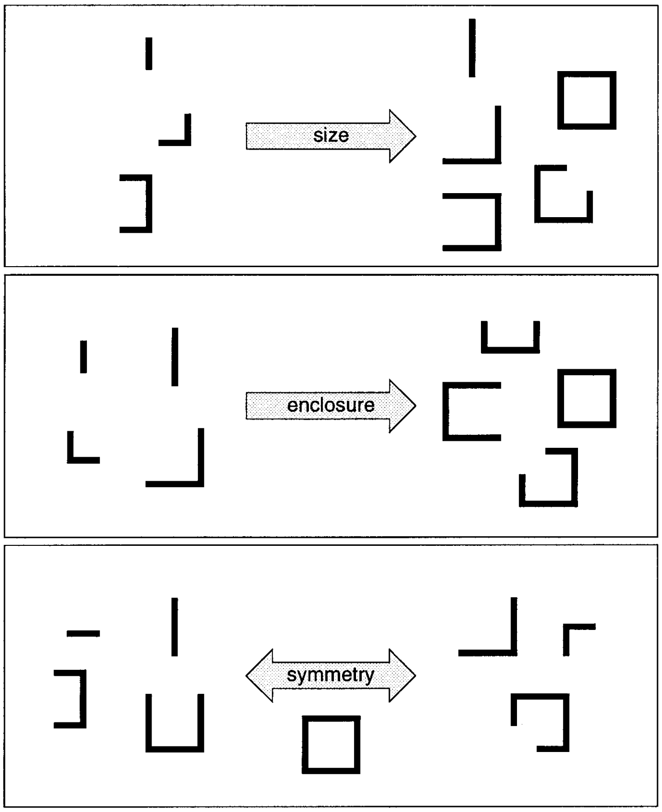


Fig. 4 Summary of object properties accounting for greatest variance in the pairwise data

both types. We note that the names that we have given to these dimensions – enclosure, size, and symmetry – are provided here primarily for descriptive convenience, and that dimensions derived from this analysis could potentially be interpreted in other ways as well.

Organization along similar dimensions may be found, albeit in different relative degrees, in the configuration space derived from subjective ratings of fit (Fig. 3B). A symmetry-related segregation of objects parallels dimension 2: objects with horizontal and vertical axes of symmetry appear at the bottom of the space, while objects with diagonal axes of symmetry appear at the top of the space. Axes roughly corresponding to the previously described dimensions of size and enclosure may be found roughly parallel to the axes of dimensions 1 and 3, respectively, though these are much less clear than they were for the configuration derived from the similarity task.

Configuration spaces derived from choice response times showed a similar general pattern: segregation of objects on the basis of enclosure could be seen in the data from the similarity task (Fig. 5A), while in the fit task, the clearest segregation was related to symmetry (Fig. 5B). Equal amounts of response time and subjective rating data were collected, but the response times were more variable from one trial to the next. Data corresponding to the same shapes had to be collapsed across orientations (e.g., objects 1 to 4, 5 to 8, etc., in Fig. 1) before organization in the configuration spaces was evident.

Significance testing by classical statistics

The statistical significance of the size, enclosure, and symmetry effects on subjective ratings and response times for the two judgments was calculated formally by classical statistical methods which echoed, quantitatively, what we have described qualitatively in the MDS configuration spaces. Since greater similarity and better fit were associated with higher subjective ratings as well as longer response times, we wished to determine the extent to which sameness or difference in the identified dimensions derived from MDS could account for the numerical ratings and response times measured for individ-

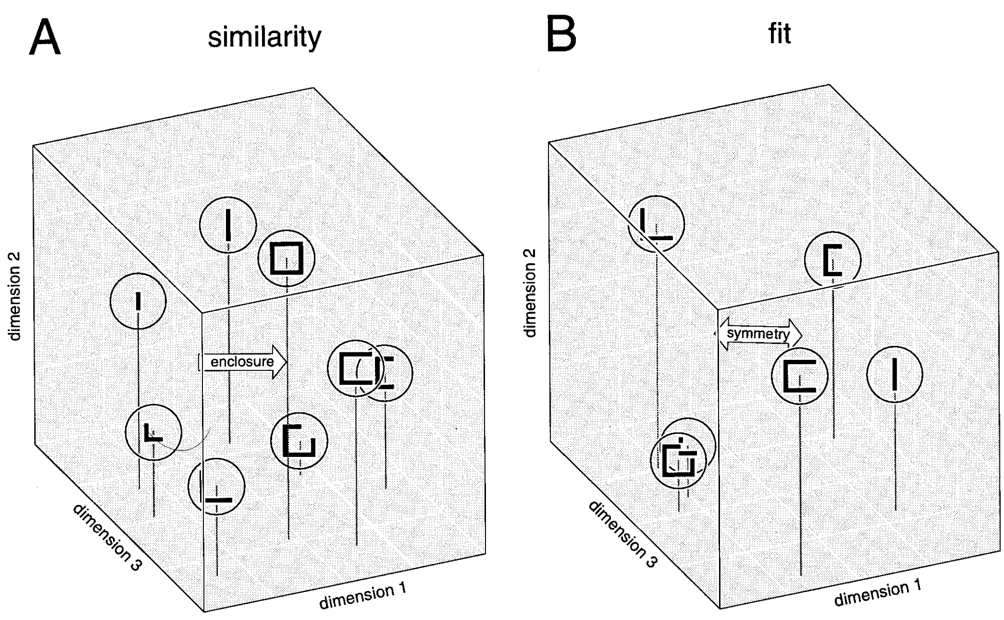


Fig. 5 Configuration spaces derived from response times in A the similarity and B the fit tasks. Each encircled symbol represents objects of the corresponding shape, collapsed across all orientations

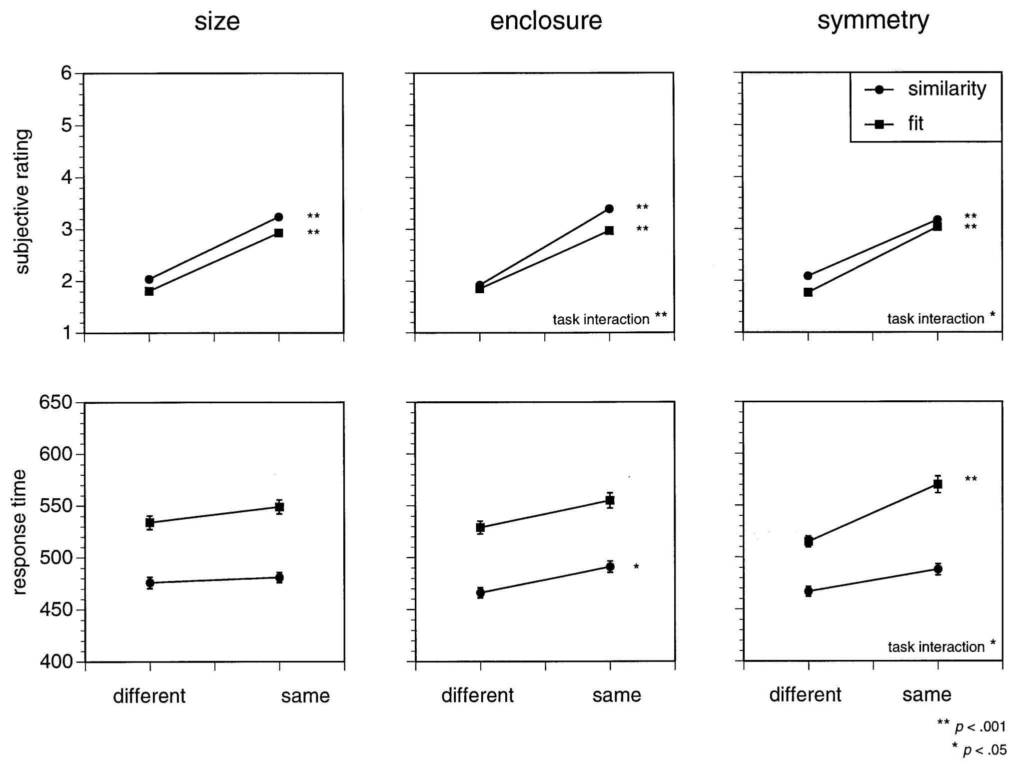


Fig. 6 Mean effects of pairwise sameness or difference in the dimensions of size, enclosure, and symmetry on subjective ratings and response times. Asterisks denote the significance levels of main effects and task interactions, as calculated by repeated measures analyses of variance

ual object pairs. We therefore used sameness or difference in size, enclosure, and symmetry (as defined in Fig. 4, following appropriate complement-transformation of data from the fit task) as two-level variables in repeated-measures analyses of variance of pairwise subjective rating and response time data.

The mean effects of each of these variables are summarized in Fig. 6. All three variables – size, enclosure, and symmetry – significantly affected subjective ratings in both the similarity and fit tasks ($P<0.0002$ for all tests). Significant interactions showed, furthermore, that the enclosure effect was greater in the similarity task than in the fit task ($F_{[1,\ 3436]}=34.6$; $P<0.0002$) and that the symmetry effect was greater in the fit task than in the similarity task ($F_{[1,\ 3436]}=7.32$; $P<0.01$). Response times in the similarity task were significantly affected by enclosure ($F_{[1,\ 1745]}=5.80$; $P<0.02$) but not by symmetry; response times in the fit task were significantly affected by symmetry ($F_{[1,\ 1366]}=15.08$; $P<0.0002$) but not by enclosure. The symmetry effect was significantly greater in the fit task than in the similarity task ($F_{[1,\ 3111]}=4.72$; $P<0.05$); the interaction between task and enclosure was not significant.

Overall, the mean effects of these three variables accounted for 3.75 (similarity task) and 3.50 points (fit task) out of the total 5-point spread on the 1-to-6 subjective rating scale. Response time effects summed to 51 ms (of 136 ms; Eq. 5) in the similarity task, and 96 ms (of 247 ms) in the fit task.

Individual differences

While the configuration spaces and mean effects that we have described thus far reflect dimensions that were common to all six subjects, there were also differences among subjects that were represented by individual weights in the INDSCAL model. Figure 7A illustrates the weight space derived from subjective rating data from the similarity task. Differences in individual strategies are indicated by differences in the relative weights of the three dimensions, which correspond to the same dimensions as in Fig. 3A. Configuration spaces derived from the data of single subjects illustrate some of those strategy differences. The configuration space of subject RW (Fig. 7B) showed clustering of objects on the basis of enclosure, while subject CE, who had small weights in all three dimensions of the common configuration space, appeared to take object orientation into account to a much greater degree than any of the other subjects. As shown in the within-subject configuration space in Fig. 7C, objects of different shapes were arranged in a gradually progressing loop defined by common orientations.

Discussion

We have applied MDS to the analysis of representations in two construction-related tasks: one involving a judgment related to copying (the similarity task), and the other involving a judgment related to assembly (the fit task). Three dimensions were identified – which we have called size, enclosure, and symmetry – that accounted for

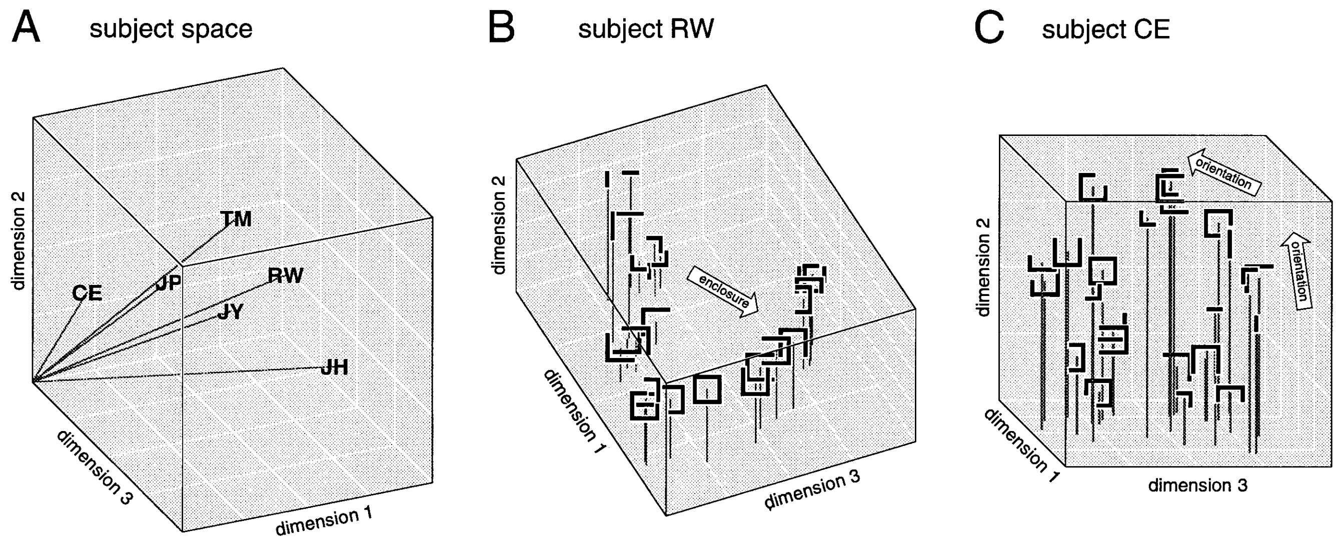


Fig. 7 Individual differences in subjective ratings of similarity, summarized in the INDSCAL weight space (A) and in configuration spaces derived from the data from individual subjects (B,C). Unlike the configuration spaces, in which relative distances between points are significant, the weight space should be interpreted according to the directions of vectors from the origin

variation in the response data from both tasks. Analyses of effects along these dimensions showed that the similarity judgments depended to a greater degree on the property of enclosure, while fit judgments on the same pairs of objects depended to a greater extent on symmetry. Analyses of two different response measures, numerical subjective ratings and choice response times, yielded qualitatively similar results. Together, they suggest that construction-related tasks depend on representations that are context-dependent, and that such representations can be usefully characterized by MDS.

Interpretation of dimensions

For convenience, we have referred to dimensions identified by MDS in terms of explicit visual analytical features. We do not claim, however, that size, enclosure, or symmetry are necessarily the primary features used in copying and assembly tasks as a general rule, or even that they are uniquely the best labels for describing the present results. The names we chose are the products of interpretation, based on the study of group and individual configuration spaces, and constrained by the properties inherent in our object set. What is important about the present method is that the dimensions themselves were derived empirically from a relatively simple experimental design, and that they identify properties that were measurably different in the two different tasks, regardless of the names given to them. It is interesting to note that the dimensions identified by MDS did not correspond to object features cited by subjects, who were each asked to describe their strategies at the conclusion of the experiment. In exploratory analyses, we found that regression models based on dimensions identified by MDS consistently resulted in better fits to the data than models based on geometric properties cited in subject reports.

We might ultimately be interested in interpreting these dimensions in terms that are functionally related to the goals of the tasks, rather than terms that are strictly visual. For example, the visual property of symmetry could be related to a functional axis of approach used in judging the fit of two objects or actually assembling them. Interpretations such as these could be disambiguated and clarified through the application of similar analytical methods to variants of the present tasks and object sets.

Subjective ratings and response times

Empirically, we observed a consistent relationship between subjective ratings and response times, whereby response times were longer for pairs of objects that were judged to be more similar to one another or closer to a perfect fit. At least two different explanations of this phenomenon are possible. An explanation based on motor set would hold that due to the difference in frequencies of “yes”? and “no” trials, subjects prepared to make the more frequent “no” response. “Yes” responses were therefore slowed, and “no” responses in the case of, e.g., similar but non-identical pairs, were delayed as subjects hesitated to commit to a choice. Another possibility is that processing time reflected increasing difficulty of judgments given more similar or better-fitting object pairs, or, obversely, that gross feature differences or incompatibilities between objects “popped out.”

The correspondence between analyses of subjective ratings and response times is interesting in two respects. First, one might regard subjective ratings as the end product of a judgment, and response time as a measure of the cognitive process that is less subject to volitional control. In that case, it is interesting that enclosure and symmetry had differential effects on both measures of the two judgments, and that, in each case, the magnitudes of the effects constituted a substantial fraction of the overall variance found in the pairwise data. Size affected subjective ratings without having any measurable effects on response times. We speculate that such measurement-dependent effects could indicate specific involvement in volitional judgments.

A second implication of the present findings is that the MDS method might be applicable to analysis of tasks involving real motions. The present study considered only movement-free analogs of construction tasks, both for the sake of simplicity and to insure that stimuli and response repertoires were strictly identical across tasks. If the method is extensible to the timing of real motions, it could be used to analyze both visuospatial and articulatory aspects of construction, as well as task-specific, kinematic deficits observed in apraxic patients (e.g., Poizner et al. 1995).

Representations, judgments, and apraxia

Human abilities to generate context-appropriate actions have been studied more frequently in their absence, in cases of apraxic deficits, than in normal function. Based on analyses of clinically associated deficits and error types, the cognitive operations underlying these disorders have been sketched out primarily in terms of broad components: e.g., ideation and execution (Barbieri and DeRenzi 1988), representation and production (McDonald et al. 1994), and visuospatial analysis and articulation (Gainotti 1985). Rothi and colleagues (1991) have argued that finer-grain models are needed to account for the full range of clinically dissociable apraxic deficits, and suggest that studies of neurologically normal subjects may play an important part in the development of a more detailed understanding of apraxia and praxis.

We suggest that the MDS approach presented here represents a useful intermediate level of analysis of the cognitive operations involved in praxis, one that is complementary to other approaches. Compared to task analyses based on hierarchies of relatively coarsely defined, layered component operations (e.g., Barbieri and DeRenzi 1988; Roy et al. 1991), the MDS approach offers a finer-grained, less model-dependent analysis of underlying representations, as well as the potential to discover dimensions of representation that may not have been anticipated pre-experimentally. Compared to analyses of kinematic variables in single tasks (e.g., Poizner et al. 1995), the MDS approach offers more detailed information about context dependence. A combination of these approaches, including behavioral and neural analysis (Whang and Georgopoulos 1997), may yield useful insights into the nature of praxis and other context-dependent abilities.

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