Using Selective Attention Theory to Design Bivariate Point Symbols

Elisabeth S. Nelson
University of North Carolina-Greensboro
Department of Geography
Greensboro, NC 27402

The research discussed in this paper applies the theory of selective attention to graphic variables used in designing map symbols. Selective attention contends that our ability to analyze a symbol's graphic variables (i.e., color, size) is affected by other graphic variables present in the same symbol. Psychological research suggests that certain combinations of graphic variables can enhance or restrict selective attention. In this literature, variables are described as either separable (capable of being attended to independently of other dimensions), integral (cannot be processed without interference from other dimensions), or configural (shows characteristics of both integrality and separability and may also form new, emergent properties). For example, sometimes it may be desirable for a map user to focus individually on separate symbol dimensions when using a bivariate or multivariate map, whereas under other conditions it may be advantageous for him/her to integrate the graphic variables visually for interpretation. Without empirical evidence describing such interactions for various combinations of graphic variables, cartographers cannot truly evaluate the functionality of the symbols they use on maps. The research reported here is the result of the first of a set of four inter-related experiments. Combinations of graphic variables were examined in an abstract setting using a speeded-classification task. Response data and accuracy data were used to provide an initial assessment of the levels of integrality, separability and configurality of several graphic combinations. Findings from this study will be integrated into subsequent map-using experiments, the results of which will assist cartographers in the design of complex map symbols.

INTRODUCTION

"Designing symbols that effectively represent geographic phenomena is one of the primary challenges in cartographic production."

Designing symbols that effectively represent geographic phenomena is one of the primary challenges in cartographic production. As with many other aspects of cartography, there are guidelines that facilitate this task, but few firm rules upon which decisions may be based. Dent (1996: 82) begins his discussion of map symbols by stating that the selection of symbols is ". . . based on a compelling system of logic tied to both the type of geographic phenomenon mapped and certain graphic primitives or variables." One of the earlier works in which such primitives are described is Bertin's *Semiologie Graphique* (1967). Bertin devised a set of six graphic variables (size, value, texture, color, orientation, and shape) that he considered to be the basic building blocks of all maps. For each of these variables, he proposed a set of rules that outlined how to best use them in conjunction with the type of data being mapped. One of Bertin's interests was in determining whether symbols, composed of various combinations of graphic variables, could be visually grouped across map space. Although his work established hypotheses about the groupings of these variables, Bertin performed little research to empirically verify his ideas. His hypotheses merit further consideration, especially given the recent interest in visualizing multivariate spatial data. One key issue, for example, is how these visual groupings interact with attentional processes. Will certain combinations of graphic variables enhance or inhibit a map user's ability to parcel out information in complex visual representations?

Psychological research in this area has emphasized the theory of *selective attention* as a way of measuring the perceptual grouping of features in a visual image. Selective attention, simply defined, is the ability to focus on a single dimension in a visual image, such as the size or value of a group of symbols, while ignoring all other symbol dimensions. Dimensions that are capable of being attended to independently of all others are *separable*; those that cannot be attended to without processing another symbol dimension as well are *integral*. A third category, *configural*, is reserved for those dimensions that may be attended to individually, but that also interact to form a relational or emergent property that takes perceptual precedence over the original dimensions.

"Psychological research . . . has emphasized the theory of selective attention as a way of measuring the perceptual grouping of features in a visual image."

The objective of this research was to empirically assess the perceptual groupings of various combinations of Bertin's graphic variables. The combinations selected were representative of those commonly found in the design of bivariate point symbols for thematic maps. The results presented here are the first in a series of four experiments designed to address the utility of selective attention for designing bivariate symbols for mapping. The overarching goal of this set of experiments is to examine combinations of graphic variables for several types of bivariate map symbols, and to do this in both non-map and map settings. The data gathered in the non-map settings is intended to replicate and expand upon previous studies conducted in psychology; the results will be used to direct the subsequent studies conducted in map settings.

Evidence from psychological studies suggests that various combinations of graphic variables may facilitate or inhibit selective attention. Such findings, if they also hold true for the perception of map symbols, would be crucial to making effective multivariate symbolization choices. Symbols composed of separable graphic variables, for example, would be expected to be effective for different types of tasks than symbols composed of integral or configural graphic variables. Cartographers have long struggled to devise effective means for graphically representing bivariate and multivariate spatial data. This research contributes to that endeavor by establishing which combinations of graphic variables are most effective for the different tasks facing the map reader in a bivariate mapping environment.

"Evidence from psychological studies suggests that various combinations of graphic variables may facilitate or inhibit selective attention. Such findings, if they also hold true for the perception of map symbols, would be crucial to making effective multivariate symbolization choices."

RELEVANT LITERATURE

Selective Attention Theory

The origins of Selective Attention Theory can be traced back to the late 1950's and early 1960's, when a number of psychological researchers (Torgerson, 1958; Attneave, 1962; Shepard, 1964) recognized that

> "the structure of the perceived relations between multidimensional stimuli depends on whether the stimulus dimensions are integral or separable, the distinction phenomenologically being between dimensions which can be pulled apart, seen as unrelated, or analyzable, and those which cannot be analyzed but somehow are perceived as single dimensions" (Garner and Felfoldy, 1970: 225).

The classic experimental task used to evaluate the interaction of stimulus dimensions is the *speeded-classification task*. In speeded classification, stimuli typically contain two graphic dimensions, where each dimension can have one of two levels. Subjects are presented with these stimuli one at a time and are asked to sort them using one of four types of discrimination tasks. In the *baseline* tasks, only one of the two dimensions (the relevant one) must be attended to in order to make a discrimination; the irrelevant dimension is always held constant. In the *filtering* tasks, the ability to sort stimuli again depends on attending to only the relevant dimension. The irrelevant dimension, however, is no longer held constant, so the

"The classic experimental task used to evaluate the interaction of stimulus dimensions is the speeded-classification task."

subject must filter out that information to perform these tasks as quickly as the baseline tasks. The *redundant* tasks are those in which both dimensions vary simultaneously; thus, discrimination can be made by attending to either dimension or by attending to both dimensions. The last task is the *condensation* task, and it requires that the subject attend to both of the stimuli dimensions to make a correct sorting decision (Bennett and Flach, 1992).

"Reaction-time performance across . . . four types of discrimination tasks provides the basis for defining three different relationships between stimulus dimensions: integral, separable, and configural."

Reaction-time performance across these four types of discrimination tasks provides the basis for defining three different relationships between stimulus dimensions: integral, separable, and configural. Two dimensions must be interdependent to be defined as integral. This interdependency is marked by such a strong interaction that the ". . . unique perceptual identities of the independent dimensions are lost" (Bennett and Flach, 1992). When such interdependency occurs, reaction times for the redundant tasks, where the two dimensions are correlated, will be faster than those for the corresponding baseline tasks (known as a *redundancy gain*). Furthermore, reaction times for the baseline tasks will be faster than those for the filtering and condensation tasks, where attention to only one or to both of the individual dimensions is required (Bennett and Flach, 1992). The former relationship is called *filtering interference* and the latter is known as *poor condensation efficiency* in the selective attention literature. Researchers using this experimental method have identified several integral stimulus dimensions (see Figure 1 for examples). One of the earlier studies, Garner and Felfoldy (1970), examined the dimensions of value and chroma and reached this conclusion. Their results have since been confirmed by Gottwald and Garner (1975), Kemler and Smith (1979), Smith and Kilroy (1979), Schumann and Wang (1980), and Smith (1980). In addition to value and chroma, psychological research has also established that the following dimensions are integral: horizontal and vertical dot position (Garner and Felfoldy, 1970; Schumann and Wang, 1980), height and width of rectangles (Felfoldy, 1974; Monahan and Lockhead, 1977; Dykes and Cooper, 1978; Dykes, 1979), and pairs of vertical lines (Lockhead and King, 1977; Monahan and Lockhead, 1977).

"Two dimensions must be interdependent to be defined as integral. This interdependency is marked by such a strong interaction that the ". . . unique perceptual identities of the independent dimensions are lost"."

Under the speeded-classification paradigm, two dimensions are defined as separable when reaction times on the baseline, filtering, and redundant tasks are equivalent. This equivalency across tasks indicates that the irrelevant dimension in each case did not interfere with subjects' abilities to attend to the relevant dimension. Since there is no interaction between the dimensions, performance on the condensation task suffers accordingly (Bennett and Flach, 1992). Psychological studies suggest that the following stimulus dimensions are separable: size and value (Handel and Imai, 1972; Gottwald and Garner, 1975; Garner, 1977; Kemler and Smith, 1979; Smith, 1980), size of circle and angle of diameter (Garner and Felfoldy, 1970; Schumann and Wang, 1980), the tilt of a line within a form (Egeth, 1966), color and orientation (Carswell and Wickens, 1990), and the orientation of multiple lines (Carswell and Wickens, 1990).

". . . two dimensions are defined as separable when reaction times on the baseline, filtering, and redundant tasks are equiva-

The third type of dimensional interaction identified in psychological studies is the configural relationship, which is viewed as an intermediate level of interaction that bridges the separable/integral continuum. In this instance, two dimensions interact to form an emerging property. Subjects can use this property ". . . as the sole basis for the classification, and thus the decision can be made more quickly than if each parent dimension were being processed sequentially" (Carswell and Wickens, 1990: 158). With this type of interaction, sorting times will again show evidence of filtering interference, but will not show evidence of redundancy gains. Furthermore, configural dimensions will facilitate the condensation task because

"". . . the configural relationship . . . is viewed as an intermediate level of interaction that bridges the separable/integral continuum."

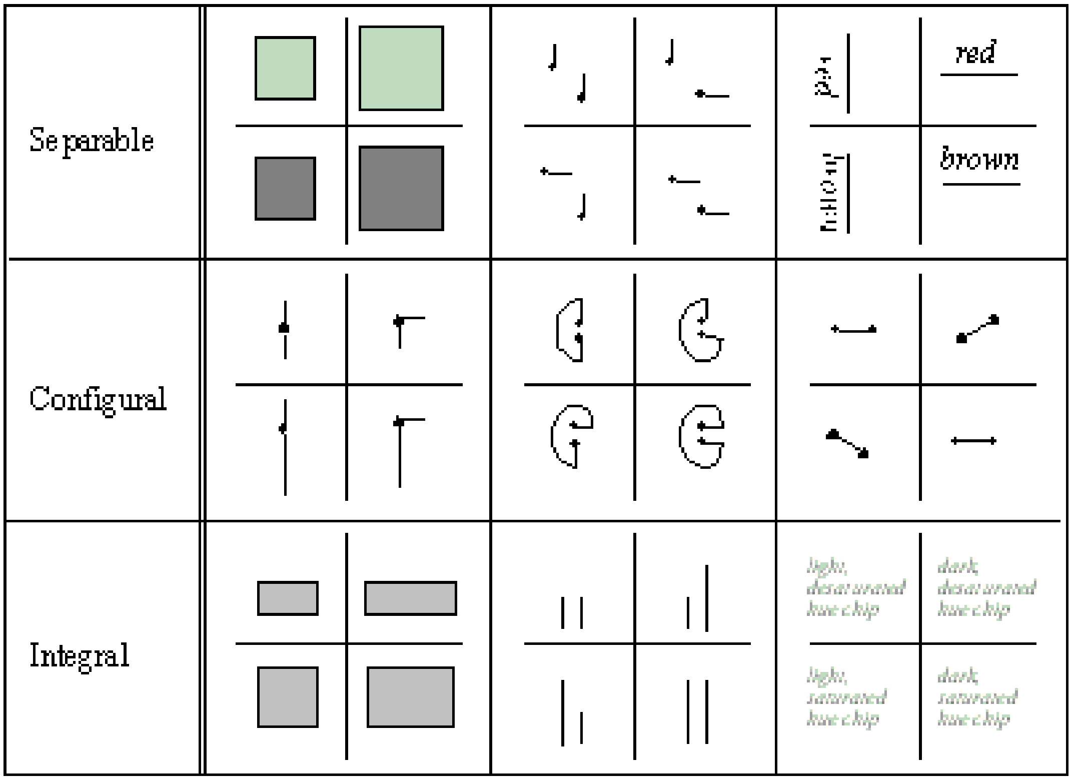

Figure 1. A few examples of stimuli tested in psychology experiments and their classification (variation in object colors is denoted by italicized labels).

the emerging property can be used as the basis for classification (Bennett and Flach, 1992). Psychological research has found that the repeated used of the same dimension promotes configurality (Garner, 1978; Carswell and Wickens, 1990). Other stimulus dimensions that have been identified as configural include vertical symmetry and parallelism (Pomerantz and Garner, 1973; Pomerantz and Pristach, 1989), as well as the vertical extents of line graphs and the orientations of folding fans (Carswell and Wickens, 1990).

Symbol Design in Cartography

Both Shortridge (1982) and MacEachren (1995) have discussed the potential relevance of selective attention to map design. Shortridge (1982: 163) notes the following about the topic:

> Psychologists expend little effort in assigning new stimuli into the separable and integral categories, but rely instead upon a small group of stimuli that already have been identified as belonging to one or the other of these categories. . . .The concepts have yet to be tested under a variety of more realistic, applied conditions, including the processing of map symbols.

MacEachren (1995) has stated that the existence of integral or separable symbol dimensions might facilitate divided or selective attention. If true, "[k]nowing which will occur in particular cases is clearly crucial to making effective map symbolization choices" (MacEachren, 1995:87).

Although cartographers have not, to date, directly tested the theory of selective attention in research on map symbolization, they have produced a number of related studies. Those relating directly to the design of point symbols fall into one of three categories: (1) those that propose designs

". . . cartographers have not, to date, directly tested the theory of selective attention in research on map symbolization . . ."

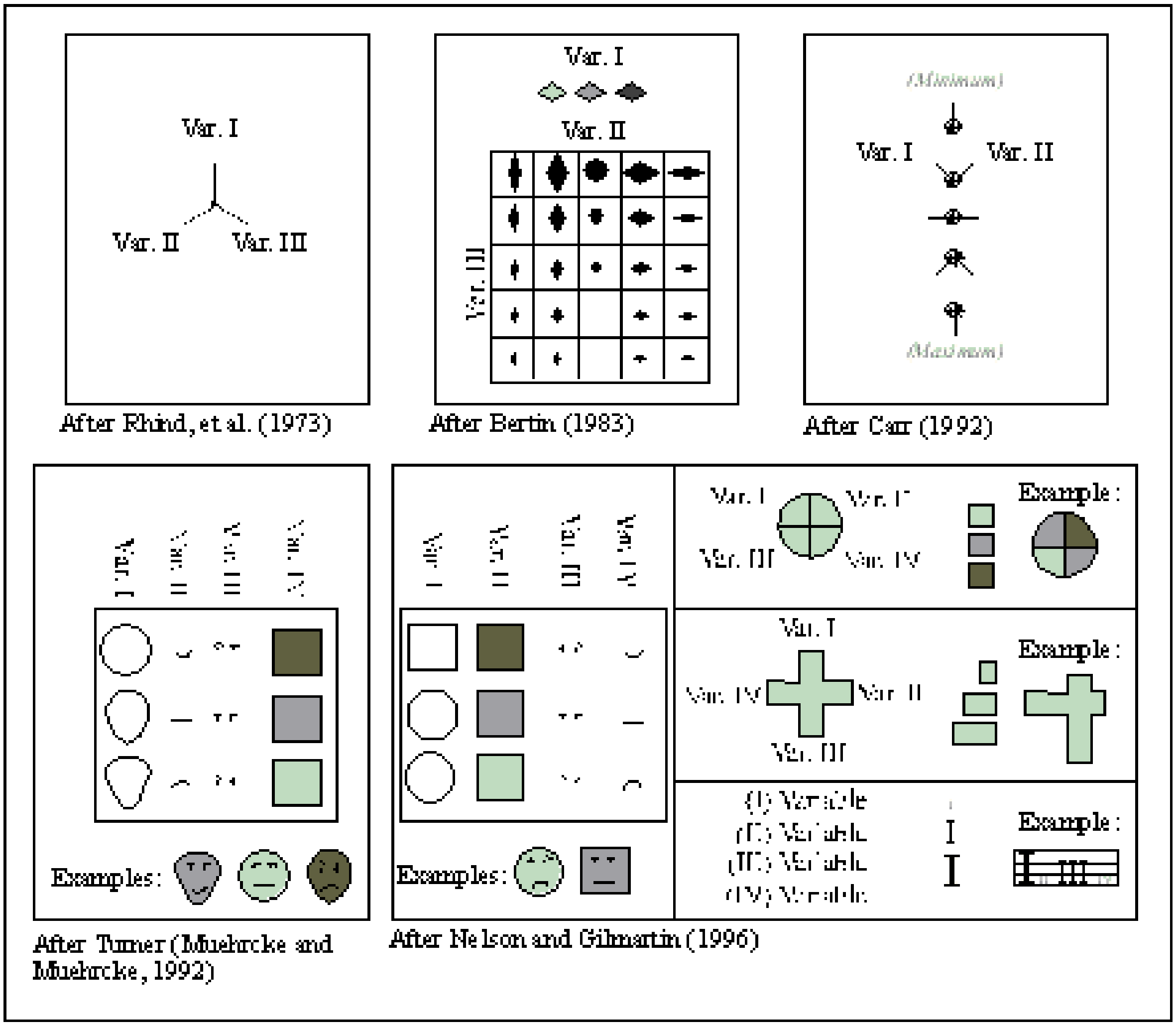

Figure 2. A few examples of multivariate symbol designs in cartography.

of multivariate point symbols; (2) those that examine the effectiveness of representing two or more variables using point symbols; or (3) those that investigate the merits of redundant coding (e.g., using two visual dimensions to symbolize one variable). These studies are reviewed below.

"A number of authors have . . . proposed designs for multivariate point symbols, but have not tested their effectiveness."

A number of authors have simply proposed designs for multivariate point symbols, but have not tested their effectiveness (see Figure 2 for examples). Carlyle and Carlyle (1977), for example, designed an ellipse that represented three variables. The number of sheep sold at various markets in Scotland was symbolized by the length of the semi-major axis of the ellipse; the distance the sheep had been transported to market was indicated by the length of the semi-minor axis; and the proportion of sales accounted for by various breeds was denoted by shading sectors of the ellipse. Bertin (1983) also discussed several ways in which multivariate data could be symbolized. Using point symbols that varied in size, value, shape, and orientation, he constructed a map that showed the distribution of three anthropomorphic characteristics of Europeans. Turner (reproduced by Muehrcke and Muehrcke, 1992: 162) created a map using Chernoff faces to symbolize four socio-economic variables for Los Angeles. A similar map showing nine quality-of-life variables for the United States was published by Wainer (1979). Bivariate ray-glyph point symbols were used by Carr to symbolize trends in sulfate and nitrate deposition in the eastern United

States (Carr, 1991; Carr, et al., 1992). Each symbol in this design consisted of two line segments joined end to end. One ray pointed left to represent sulfates, and one pointed right to indicate nitrates. The angle of the lines away from vertical symbolized the rate of increased or decreased deposition per year. Dahlberg (1981) combined circle size and shading value in a bivariate point symbol to illustrate the number of course offerings in cartography and the relative importance of cartography programs at U.S. colleges and universities.

Two studies have investigated the effectiveness of quantitative multivariate point symbols from an empirical perspective. Rhind, et al. (1973) designed a three-arm wind-rose type symbol for summarizing geochemical data. The length of each arm represented the concentration of copper, lead, and zinc in stream sediments, with symbol location on the map indicating where the sediment samples had been collected. The authors used both counting and estimation tasks to determine how well the symbol would function under varying scale and background conditions. Results of their study suggested that none of the experimental variables had much effect and that subjects performed poorly under all conditions.

"Two studies have investigated the effectiveness of quantitative multivariate point symbols from an empirical perspective."

Nelson and Gilmartin (1996) evaluated four different multivariate point symbol designs by measuring how quickly and accurately map readers could retrieve either an individual value from a symbol or interpret the symbol's overall (composite) value. They also asked map readers to discern regional trends by examining groups of these symbols. The symbols evaluated included two abstract, geometric designs (crosses and circles), Chernoff Faces, and a rectangular symbol containing graduated alphabetic characters that represented the mapped variables. Results of their study suggested that subjects could answer questions using all symbol types with the same level of accuracy, if given enough time. There was a clear hierarchy, however, in how difficult each symbol was to process. Subjects found it easiest to reach a correct answer using the boxed letters and most difficult to reach a correct answer using the Chernoff Faces. Furthermore, reaction times for questions about specific parts of both Chernoff Faces and boxed letters were processed more quickly than questions that required the subject to process each symbol as a whole. This suggests that subjects could focus more quickly on an individual component of these symbols than on their composite image. The opposite held true for the geometric symbols tested.

"Other cartographers have examined the efficacy of redundant coding in map symbolization."

Other cartographers have examined the efficacy of redundant coding in map symbolization. Dobson (1983), for example, investigated the utility of redundant coding on graduated symbol maps. He added gray-tone shading to proportional circles to assess whether varying the value as well as the size of a map symbol would improve map interpretation. The greater the quantity represented by the circle, the larger the circle was in area and the darker the shading was within the circle. He found that the redundant symbolization resulted in subjects responding more quickly and accurately, which is a somewhat surprising result, given that selective attention studies indicate that size and value are separable dimensions. It may be that people, if asked, can ignore either dimension but do not necessarily do so spontaneously - especially when both dimensions represent the same variable, as they did in Dobson's study. Or as MacEachren has proposed, the apparent redundancy gain may be a function of experimental design (subjects had to search for a specific symbol among other symbols and then interpret it) rather than a pure reflection of classification speed (1995:89).

"Research on multivariate symbols that is structured so as to identify integral, separable, and configural graphic dimensions would provide cartographers with guidance on how to design maps meant to be read in specific ways."

None of the studies cited here were planned with the theory of selective attention in mind, but the concept could easily have been incorporated into most of their designs. Research on multivariate symbols that is structured so as to identify integral, separable, and configural graphic dimensions would provide cartographers with guidance on how to design maps meant to be read in specific ways. For example, if a map author wants readers to see how mapped variables co-vary with each other, he or she might devise a symbolization system composed of integral graphic dimensions. Conversely, if the cartographer's goal is to represent two or more thematic variables so that the variables' individual characteristics can be retrieved, then the symbol should consist of separable visual dimensions. If retaining both aspects of the data is desirable (individual values as well as correlations), then configural symbols could be employed.

RESEARCH METHODS

This study was designed to test subjects' abilities to selectively attend to various combinations of graphic variables (e.g., symbol dimensions) that might comprise bivariate point symbols on thematic maps. As the first step in a multi-phase research project, this experiment focuses specifically on point symbolization. Testing took place in an abstract as opposed to cartographic setting. The methodology and analyses used in this experiment were patterned closely after those reported in psychological studies of selective attention (see Carswell and Wickens, 1990, for example). The stimuli, however, unlike most of those tested in psychology, were designed with their potential relevance for cartographic use in mind.

"This study was designed to test subjects' abilities to selectively attend to various combinations of graphic variables . . . that might comprise bivariate point symbols on thematic

Symbol Sets

Twelve symbol sets were created using those graphic variables most commonly employed in cartographic design (Figure 3). Note that these sets do not include all possible pairings of the graphic variables - only those that seemed most applicable to map design. Furthermore, these sets include two types of pairings: homogeneous (where a graphic variable is paired with itself) and heterogeneous (where two different graphic variables are paired) (Garner 1978; Carswell and Wickens 1990). Since every set was composed of two graphic variables, each of which varied on two levels, four individual symbols comprised each set. In Figure 4, for example, levels 1 and 2 (light and dark shading) of dimension 1 (value) are represented in the upper and lower rows of cells of the graphic. Levels 1 and 2 (small and large) of dimension 2 (size) are in the right and left columns of the cells.

"Twelve symbol sets were created using those graphic variables most commonly employed in cartographic design."

Tasks

Each symbol set was tested using a battery of speeded classification tasks to assess incidents of separability, integrality, and configurality among the different combinations of graphic variables. The nine tasks that made up the speeded-classification battery are summarized in Figure 2. Baseline tasks provided baseline reaction times for all classifications that could be made by examining only one of the two symbol dimensions. Filtering tasks assessed the ability of subjects to classify symbols by examining one of the two symbol dimensions when the additional dimension varied randomly. Redundancy tasks assessed the ability of subjects to classify symbols when they were defined by redundantly paired dimensions. Condensation tasks required subjects to attend to both dimensions of the symbol to classify it correctly (Carswell and Wickens, 1990).

"Each symbol set was tested using a battery of speeded classification tasks to assess incidents of separability, integrality, and configurality among the different combinations of graphic variables."

Hypotheses

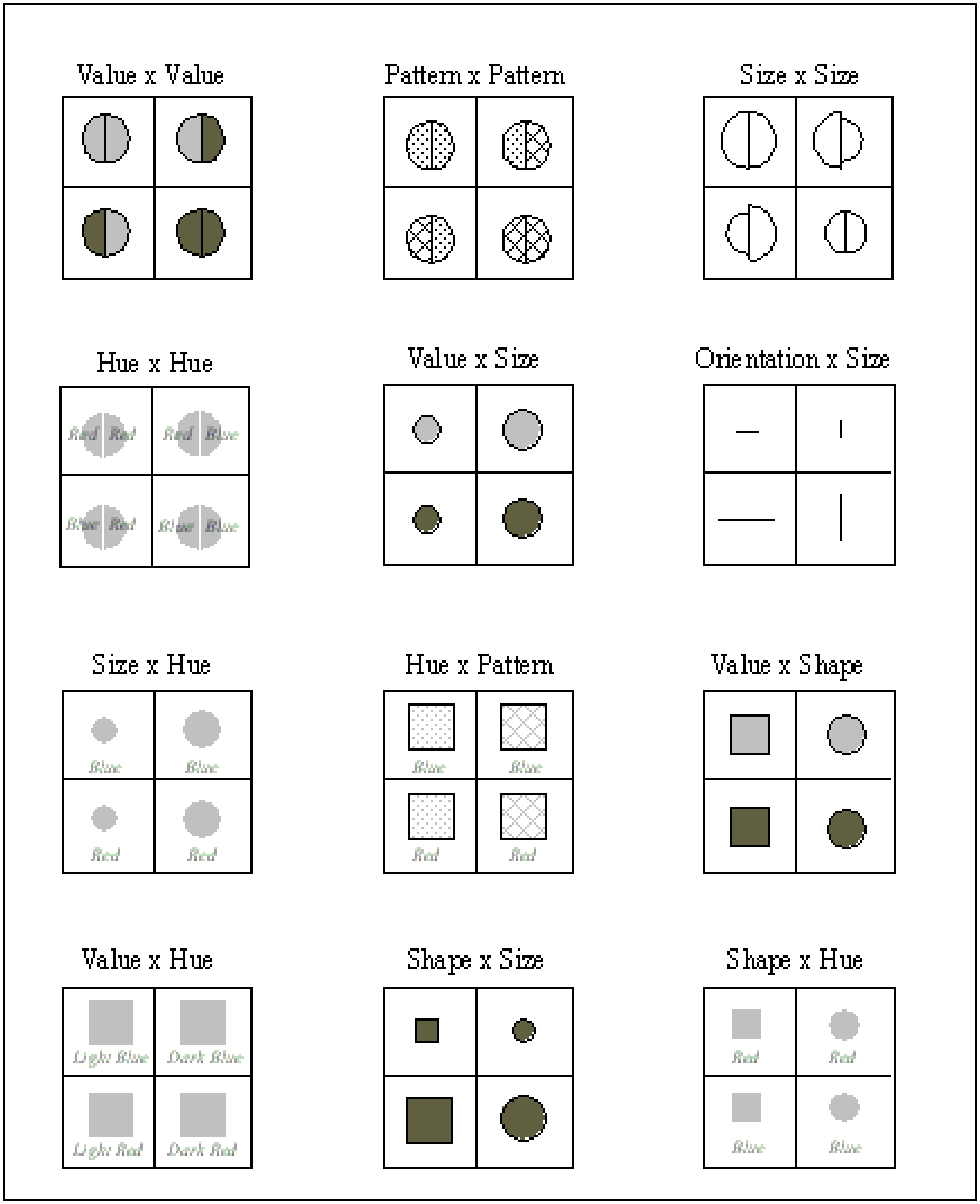

Figure 3. Symbol Sets

The primary question asked during this experiment was whether subjects would be able to attend to one dimension of a symbol while ignoring the other. For dimension 1 in Figure 4, then, the question was: Can subjects attend to the shading value of the circle and ignore its size? For dimension 2, a similar question was posed: Can subjects focus their attention on circle size, regardless of the shading value? The battery of speeded-classification tasks was designed to provide data to answer these questions. The following research hypotheses were posed on the basis of results of several psychological studies:

- The graphic combination of size and value should behave as separable dimensions (Handel and Imai, 1972; Gottwald and Garner, 1975; Garner, 1977; Kemler and Smith, 1979; Smith, 1980). For analysis purposes, this means that reaction times for the baseline, filtering, and redundancy tasks will be equivalent; those for the condensation task will show an increase relative to the reaction times for the filtering tasks.

- Graphic combinations that are homogeneous should behave as configural dimensions (Garner, 1978; Carswell and Wickens, 1990). For this to be true, reaction times for the baseline and redundancy tasks must be equivalent. Furthermore, reaction times for filtering tasks must show an increase relative to the baseline tasks, while condensation tasks must show a decrease relative to the reaction times for the filtering tasks.

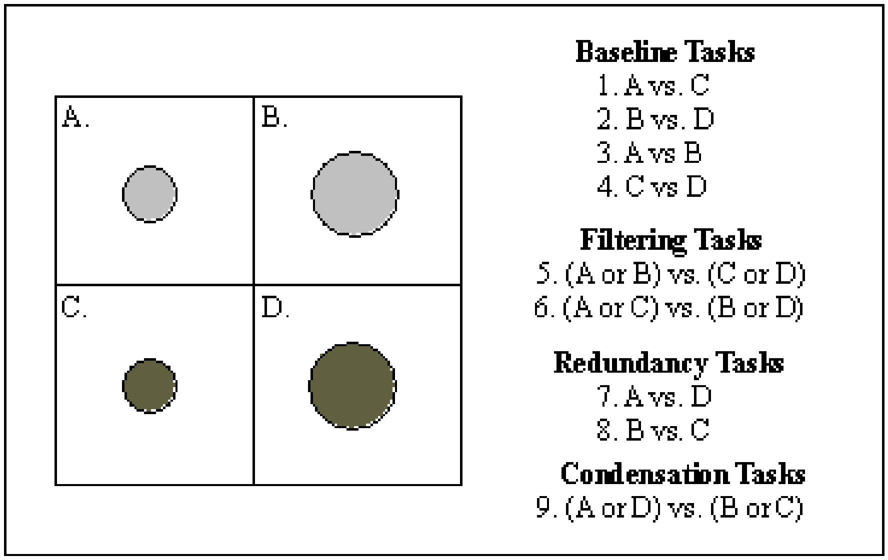

Figure 4. Speeded-classification tasks used to diagnose separability, integrality, and configurality (after Carswell and Wickens, 1990).

Subjects

Ninety subjects participated in the experiment. Subjects were solicited from the student population at San Diego State University.

"Each subject performed nine different speeded-classification tasks for four of the twelve symbol sets."

Test Procedure

Each subject performed nine different speeded-classification tasks for four of the twelve symbol sets. Both the presentation and the collection of data were controlled by computer. For each symbol set seen, the subject performed two replications of nine blocks of trials, where each block was associated with one of the nine tasks outlined in Figure 4. The first set of trials for each block was considered a practice trial; therefore, it was not used in the analysis of the data collected. The order of the symbol sets and the order of the blocks for each symbol set were randomized for each subject and each replication.

The procedure for testing was automated by carefully coding the necessary sequence of events using Visual Basic on a Windows/NT operating system. Following the initial instructions of the experimenter, which outlined the central idea and methodology of the experiment to the subject, the computer program was executed. The program presented the subject with a classification rule associated with one of the nine tasks and examples of the four symbols in the symbol set being tested (labeled A, B, C, and D). For example, if the task was one of the filtering tasks, the subject might have been instructed to press the left arrow key if the presented symbol was A or B, and to press the right arrow key if the presented symbol was C or D (Figure 5a). The symbols for the block of trials was then presented on-screen one at a time in a random order (Figure 5b). Each symbol remained on-screen until the subject classified it by pressing one of the two arrow keys. If it was classified incorrectly, the computer responded with a beep to alert the subject. At the end of each block of trials, subjects were given feedback on their performance in two forms: the percentage of classifications they correctly completed and their mean

"Reaction times and error rates for each symbol set were recorded for analysis."

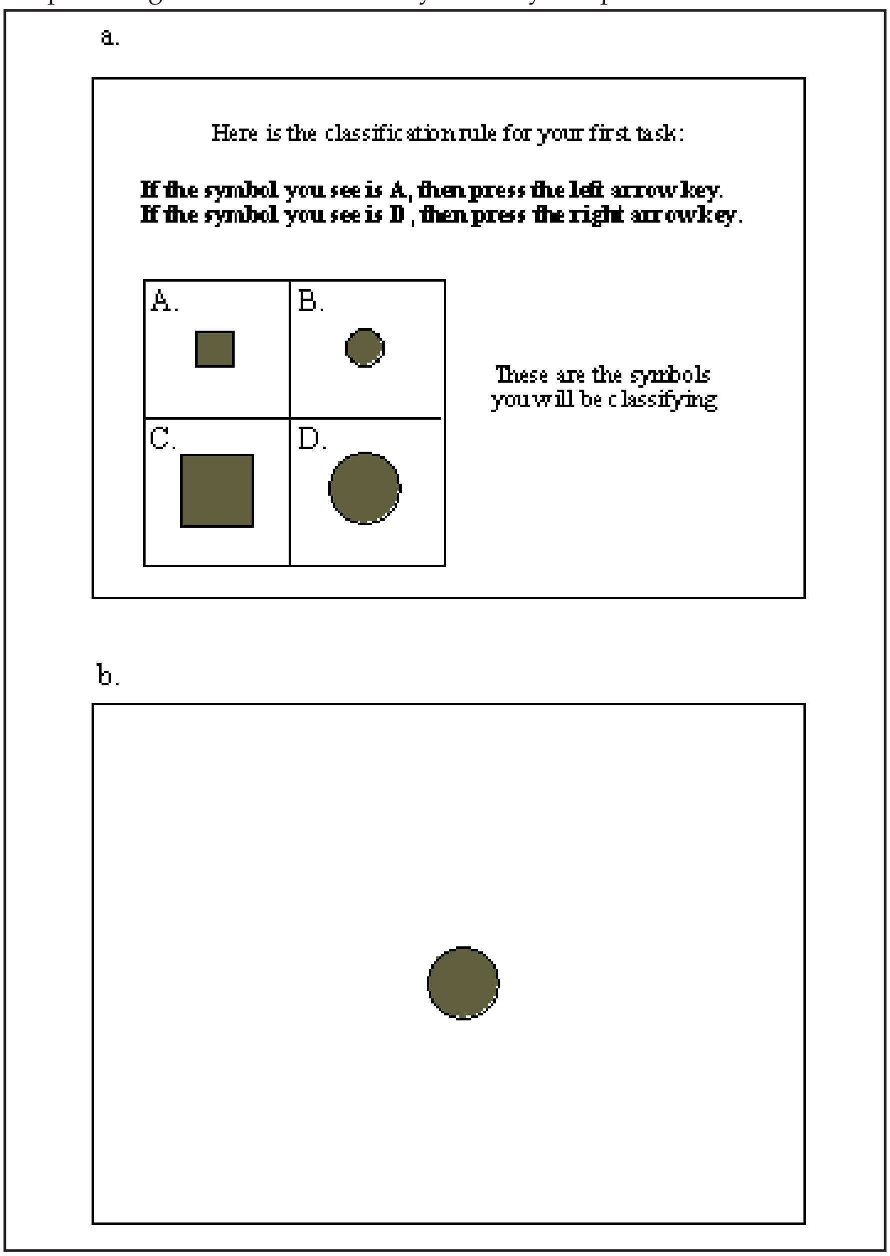

Figure 5. Experimental Design. (a) shows the presentation of a classification rule and symbol set. (b) shows an actual test screen that required the subject to classify the symbol on the basis of the rule given in (a).

DATA ANALYSIS

correct response time. When the nine blocks were completed for a given stimulus set, subjects were allowed to take a short break before beginning the test for the next set of symbols. Reaction times and error rates for each symbol set were recorded for analysis.

Two types of analyses were performed on the data collected. First, the data for each symbol set was subjected to an analysis of variance (ANOVA), where the dependent variables were reaction time and percent error. The purpose of these analyses was to evaluate the prevalence of separable, integral, and configural interactions among the combinations of graphic variables comprising each symbol set. Since an ANOVA treats such interactions as discrete (either a symbol set is separable, integral, or configural), these analyses were supplemented with a principal components analysis (PCA), which used a set of summary measures derived from the collected data as input. The inclusion of this analysis allowed the dimensional interactions of the symbols to be assessed along a continuum. This is important, since some combinations of graphic variables may not be strongly configural, integral, or separable, but may have characteristics that place them somewhere in-between these definitions. Principal components analysis plays upon the idea of a continuum of characteristics by locating each symbol set within a multivariate space. The distribution of sets within the space is defined by the summary measures used to create it. Their locations should indicate which sets are more similar to one another on the basis of the defined dimensional interactions and which dimensional interactions best characterize those that are grouped together.

"Mean reaction time and percent error served as the dependent variables in separate analyses for each symbol set."

Analyses of variance

Reaction time data were first explored using a univariate analysis. Incorrect responses were set to missing data, and extreme values (as defined by Tukey's Hinges (SPSS, 1997)) were deleted. These steps eliminated 14 of 100,224 responses. Since the data were skewed for each symbol set, the geometric means for the remaining data were computed by averaging all subject responses across all categories. Percent error data were also obtained by aggregating all subject responses across all categories.

Mean reaction time and percent error served as the dependent variables in separate analyses for each symbol set. The independent variable in each case was task (nine levels). The main effect of task was significant for all reaction time analyses ($p < 0.0001$). Corresponding analyses for percent error were not significant. Percent error for all tasks was low (on the order of 3 percent) and produced no significant differences in any of the task comparisons, so these analyses are not reported. A set of planned comparisons between tasks for the reaction time data was used to assess incidents of separable, integral, and configural interactions for each symbol set (Table 1).

"A set of planned comparisons between tasks for the reaction time data were used to assess incidents of separable, integral, and configural interactions for each symbol set."

Table 2 presents the mean reaction times used to evaluate the effects of filtering tasks on each symbol set. Filtering tasks required subjects to classify symbols on the basis of one dimension while the second dimension varied randomly. For four of the twelve symbol sets (value/value, pattern/pattern, size/size, hue/hue), completion of these tasks took significantly longer than completion of corresponding baseline tasks. This indicates that for these combinations of graphic variables the irrelevant dimension could not be ignored during classification. For symbol sets comprised of orientation/size, value/hue, hue/pattern, and shape/size, analyses suggested subjects could effectively ignore one of the dimensions during filtering tasks, but not the other. Symbols defined by a value/hue combination, for example, exhibited reaction times suggesting that subjects could effectively ignore differences in value when asked to classify symbols on the basis of hue. They apparently could not, however, ignore

Task Comparison*	A significant difference indicates this type of dimensional interaction: Separable	Configural	Integral
mean $RT_{(T1, T2)}$ vs. mean $RT_{(T5)}$		✓	✓
mean $RT_{(T3, T4)}$ vs. mean $RT_{(T6)}$		✓	✓
Faster of mean baseline tasks vs. mean $RT_{(T7)}$			✓
Faster of mean baseline tasks vs. mean $RT_{(T8)}$			✓
mean $RT_{(T5, T6)}$ vs. mean $RT_{(T9)}$	✓ †	✓	✓ ††

* T1 = Task 1, T2 = Task 2, etc.
†T9 has significantly longer response times
††T9 has significantly shorter response times

Table 1. Planned comparisons for ANOVAs

Symbol Set *(D1 x D2)*	**Mean Reaction Time (milliseconds)** *Dimension 1(D1)* Baseline Tasks	Filtering Tasks	Sig.	*Dimension 2 (D2)* Baseline Tasks	Filtering Tasks	Sig.
Value x Value	424	478	**.000**	412	498	**.000**
Pattern x Pattern	441	503	**.000**	428	523	**.000**
Size x Size	368	469	**.000**	399	523	**.000**
Hue x Hue	424	478	**.000**	412	483	**.000**
Value x Size	455	459	.752	388	395	.945
Orientation x Size	388	473	**.000**	350	361	.846
Size x Hue	403	420	.366	388	388	1.000
Hue x Pattern	420	441	062	416	441	**.002**
Value x Shape	437	441	.970	399	399	1.000
Value x Hue	407	424	.187	424	469	**.000**
Shape x Size	380	424	**.000**	392	407	.401
Shape x Hue	392	399	.694	384	384	1.000

Table 2. Analysis of Filtering Interference

hue when asked to classify symbols of the basis of value. Four sets (value/size, size/hue, value/shape, shape/hue) showed no indication of having any dimensional interactions for this type of task.

Significant increases in response times for filtering tasks relative to the mean baseline reaction times suggest that some form of dimensional interaction occurred between the graphic variables comprising those symbols. To further parse these symbol sets into integral and configural groups, subject performance was examined for redundancy tasks. In these tasks both dimensions of the symbol were varied simultaneously, allowing a correct classification to be made by attending to either dimension or by attending to both dimensions. Table 3 presents the mean reaction times used to evaluate the effects of redundancy tasks on each symbol set. Response

"Significant increases in response times for filtering tasks relative to the mean baseline reaction times suggest that some form of dimensional interaction occurred between the graphic variables comprising those symbols."

". . . none of the graphic combinations tested clearly produced an advantage when varied together simultaneously. This suggests that none of these symbol sets can be categorized as strictly integral."

Symbol Set *(D1 x D2)*	**Mean Reaction Time (milliseconds)** *Dimension 1(D1)* Faster Baseline	Positive Redundancy	Sig.	*Dimension 2 (D2)* Faster Baseline	Negative Redundancy	Sig.
Value x Value	412	407	.986	412	403	.597
Pattern x Pattern	428	416	.433	428	420	.655
Size x Size	369	380	.536	369	351	**.041**
Hue x Hue	412	392	**.003**	412	412	1.000
Value x Size	388	384	.997	388	424	**.000**
Orientation x Size	351	347	.982	351	321	**.000**
Size x Hue	384	369	.123	384	392	.882
Hue x Pattern	416	403	.467	416	416	1.000
Value x Shape	395	392	.954	395	399	.990
Value x Hue	407	403	.983	407	403	.984
Shape x Size	380	365	.400	380	365	.244
Shape x Hue	384	369	.203	384	376	.953

Table 3. Analysis of Redundancy Gains

Symbol Set (D1 x D2)	**Mean Reaction Time (milliseconds)** Filtering Tasks	Condensation Task	Sig. (Decrease ↓ Increase ↑)
Value x Value	488	455	.000 ↓
Pattern x Pattern	513	469	.000 ↓
Size x Size	498	433	.000 ↓
Hue x Hue	483	446	.000 ↓
Value x Size	428	602	.000 ↑
Orientation x Size	416	561	.000 ↑
Size x Hue	403	596	.000 ↑
Hue x Pattern	441	614	.000 ↑
Value x Shape	420	620	.000 ↑
Value x Hue	446	572	.000 ↑
Shape x Size	416	572	.000 ↑
Shape x Hue	392	584	.000 ↑

Table 4. Analysis of Condensation Efficiency

times for these tasks relative to the faster of the mean baseline reaction times indicate that none of the graphic combinations tested clearly produced an advantage when varied together simultaneously. This suggests that none of these symbol sets can be categorized as strictly integral. Three of the twelve sets (size/size, hue/hue, and orientation/size) showed significant decreases in response times from their baselines for either a positive or negative correlation of dimensions, but not both. The value/size combination showed a significant redundancy effect in the negative correlation of dimensions, but this was a significant increase in response time relative to the baseline, not decrease.

". . . condensation efficiency tasks . . . required subjects to attend to changes in both graphic variables in order to make a correct classification decision."

Response times used to evaluate symbol set performance on condensation efficiency tasks are presented in Table 4. This task required subjects to attend to changes in both graphic variables in order to make a correct classification decision. Symbol sets that show a significant increase in response times for this task, when compared to corresponding filtering tasks, are comprised of variables that do not interact to facilitate classification. This occurrence, when coupled with no significant filtering interference or redundancy gains, suggests the symbol is separable. Those symbol sets that behaved in this manner include size/hue, value/shape, and shape/hue. When symbol sets show a significant decrease in reaction times in conjunction with significant filtering interference but no significant redundancy gains, then the symbol is configural. Those sets that clearly behaved in this manner were value/value and pattern/pattern. The remaining sets did not fall clearly into any one of the three categories.

"Seven summary measures, first defined in Carswell and Wickens (1990), were used as the basis for this analysis."

Principal components analysis

Measure	Derivation*
Total Discriminability	mean $RT_{(T1,T2)}$ + mean $RT_{(T3,T4)}$
Relative Discriminability	| mean $RT_{(T1,T2)}$ - mean $RT_{(T3,T4)}$ |
Redundancy Gain	((Faster of mean baseline tasks/mean $RT_{(T7)}$) + (Faster of mean baseline tasks/mean $RT_{(T8)}$))/2
Redundancy Asymmetry	| (Faster of mean baseline tasks/mean $RT_{(T7)}$) - (Faster of mean baseline tasks/mean $RT_{(T8)}$) |
Filtering Interference	((mean $RT_{(T5)}$/mean $RT_{(T1,T2)}$) + (mean $RT_{(T6)}$/mean $RT_{(T3,T4)}$))
Filtering Variability	mean standard deviation of filtering tasks
Condensation Efficiency	((Slower of mean baseline tasks/mean $RT_{(T9)}$)

* T1 = Task 1, T2 = Task 2, etc.

Table 5. Summary Measures for the Principal Components Analysis

Seven summary measures, first defined in Carswell and Wickens (1990), were used as the basis for this analysis (Table 5). These measures provide several characterizations of the dimensional interactions that occurred between the graphic variables comprising each symbol set. Total Discriminability, for example, represents the mean response time required to perform baseline tasks for a symbol set. Longer response times suggest that subjects had more difficulty perceiving perceptual differences within each symbol dimension during classification. Relative Discriminability measures the mean difference in response times for baseline tasks. Larger differences in response times indicate that subjects were able to classify symbols on the basis of one graphic variable more easily than the other. Thus, one would expect that the two dimensions are not equally perceptible. Redundancy Gain measures the ability of redundant variation in both dimensions of a symbol set to improve symbol classification. Larger values of this measure indicate that this property enhanced discrimination between symbols during classification. Redundancy Asymmetry measures the amount of perceptual discrimination that occurs between symbols showing positively correlated dimensions and those showing negatively correlated dimensions. Larger values here suggest that response times for classifying these two types of symbols were more disparate, meaning that redundant variation enhanced discriminative ability in one direction but not the other. Filtering Interference measures how easily irrelevant dimensions can be ignored during classification tasks. Higher values for this measure indicate that irrelevant dimensions cannot easily be ignored. Filtering Variability is a measure of between-subject variability for the filtering tasks. Higher values for this measure indicate increased performance variability for filtering tasks. One possible cause for this may be that some subjects make use of emergent features within a symbol to enhance discriminative ability during classifications, while others do not. Finally, Condensation Efficiency is a measure of how easy it is for subjects to attend to all the dimensional interactions to differentiate symbols. Larger values here suggest that it is more difficult to classify symbols correctly when all dimensional interactions must be considered. These measures were computed for each of the 12 symbol sets and used as input into the principal components analysis. Table 6 presents the component loadings for the first three principal components. These are orthogonally rotated components with eigenvalues of 2.5, 2.0, and 1.7 respectively. Collectively, they account for 88% of the variance among the seven original measures.

"Component I . . . appears to be describing dimensional perceptibility."

Component I reveals a cluster of three variables that have high positive loadings: relative discriminability, redundancy asymmetry, and filtering variability. In addition, redundancy gain has a moderately strong negative loading. This component appears to be describing dimensional perceptibility. High values of relative discriminability indicate that the symbol dimensions varied considerably in subjects' abilities to use them for classification. Strong redundancy asymmetry and filtering variability, along with the negative loading of redundancy gains, emphasize that perceptual inconsistency. If the two dimensions are not equally perceptible, for instance, it follows that redundant variation for the purposes of enhancing symbol discrimination will be asymmetrical at best and that filtering out

Summary Measures	Component I	Component II	Component III
Relative Discriminability	.91	.03	-.14
Redundancy Asymmetry	.85	-.10	-.01
Filtering Variability	.67	.67	-.01
Filtering Interference	-.04	.11	.98
Condensation Efficiency	-.09	-.23	.96
Total Discriminability	-.13	-.89	.09
Redundancy Gain	-.45	.84	-.02

Table 6. Rotated Component Loadings for the Principal Components Analysis

one dimension over the other may be more difficult during the filtering tasks. Those symbol sets that had the highest scores for this component were value/size, size/size, and orientation/length. Those that scored the lowest for this component included shape/hue, shape/size, pattern/pattern, and value/value (Figure 6).

". . . Component II . . . seems to be describing perceptibility within each symbol dimension."

The strongest positive loadings for Component II were redundancy gain and filtering variability. These are coupled with total discriminability, which loaded negatively for the component. This component seems to be describing perceptibility within each symbol dimension. The bi-polar relationship that exists between redundancy gain and total discriminability suggests an inverse relationship between subjects' abilities to perceive differences within the symbol dimensions comprising the symbol and their ability to use redundant variation of those dimensions to enhance perceptibility during classification. According to this component, those symbol dimensions that have distinct perceptual differences within each dimension (low total discriminability) are the best able to utilize redundant variation (high redundancy gain). They also seem to be associated with strong levels of filtering variability, suggesting that these sets may be associated with the ability to form emergent properties that some subjects my have used to facilitate classification where others did not. Those symbol sets with high scores for this component include orientation/size, shape/hue, and size/size. Those with the lowest scores were value/size, pattern/pattern, hue/pattern, and hue/hue.

"Component III . . . represents a general configurality component."

Component III has only two strong loadings and both are positive. High values of filtering interference and condensation efficiency, coupled with a very low positive loading for redundancy gains suggest that this

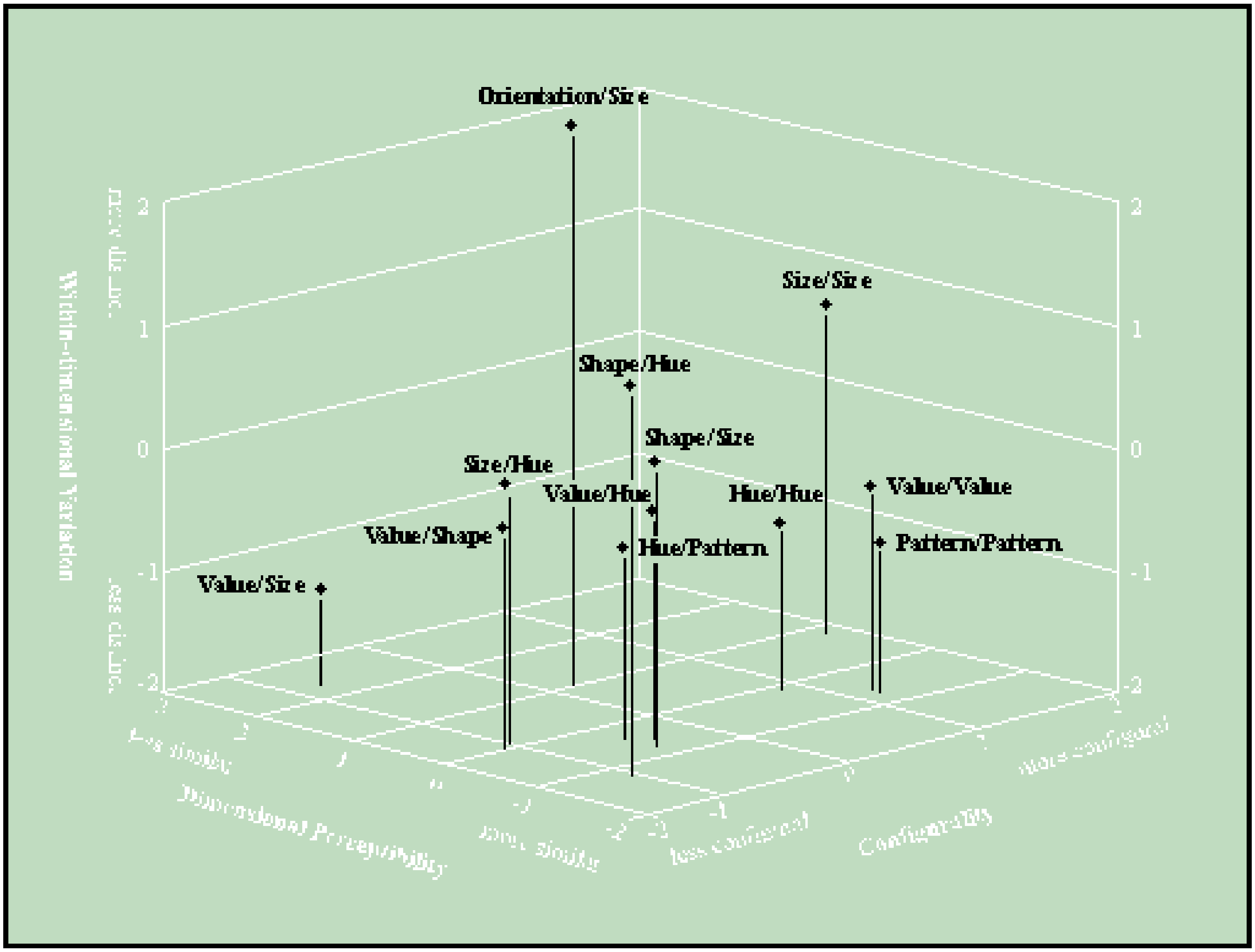

Figure 6. Principal Components Analysis

axis of the multivariate space represents a general configurality component. Here symbol sets that are comprised of dimensions that cannot be ignored during classification are also associated with an ability to use all dimensional interactions together to enhance classification ability. Those sets with high scores on this component were hue/hue, pattern/pattern, value/value, and size/size. Value/size, size/hue, shape/hue, and value/hue were the symbol sets with the lowest scores for this component.

DISCUSSION

The theory of selective attention proposes that there are three distinct interactions that occur when symbols in a visual image, such as a map, are perceptually grouped. In the first case, the dimensions of the symbol in question may be attended to individually of each other, creating separate perceptual groupings for each dimension. At the opposite end of the spectrum, the dimensions of the symbol are completely interdependent, resulting in an integral interaction of symbol dimensions. Here, one cannot perceptually process one dimension without taking the second into consideration as well. The third category, configurality, represents a midpoint between these two extremes. In this instance, the dimensions of a symbol may interact to form a third, emergent property for the symbol. Perceptual grouping may then occur using this emergent property or each parent dimension may be processed separately, depending on the map

“. . . only two . . . interactions were clearly identified for the symbol sets tested using a speeded-classification task: separability and configurality.”

user's goals.

In this study, only two of these interactions were clearly identified for the symbol sets tested using a speeded-classification task: separability and configurality. The lack of integral interactions is interesting, but not necessarily disturbing. Although several psychological studies have purported to find integral dimensions in their speeded-classification testing, researchers in that field are now questioning those results (Carswell and Wickens, 1990; Carswell and Wickens, 1988; Casey and Wickens, 1986; Jones and Wickens, 1986). These researchers have found that graphs composed of supposedly integral dimensions do not necessarily enhance the processing of correlated variables, as would be expected. This has led to the proposal that many of these dimensions might actually be more configural than integral, with an emergent feature providing users with a perceptual shortcut for integrating information when required (Barnett and Wickens, 1988; Coury and Purcell, 1988; Sanderson, et al., 1989).

"Of the twelve symbol sets tested, three are clearly separable . . . size/hue, value/shape, and shape/hue."

Of the twelve symbol sets tested, three are clearly separable according to the ANOVAs: size/hue, value/shape, and shape/hue. These findings are further supported by the results of the principal components analysis (PCA). Although these graphic combinations are mixed with respect to dimensional perceptibility and within-dimensional variation, they all are clearly grouped at the low end of the configurality axis. The PCA also suggests that value/size is separable, which supports the first hypothesis for this study. Generally, the ANOVA supports this, although it is an imperfect fit. While there is no evidence of filtering interference and condensation efficiency is poor, there is a significant redundancy decrement that does not fit the overall pattern for separability. From a cartographic perspective, this decrement is actually rather interesting. Apparently, when size and value were positively correlated (low value/small size versus high value/large size) subjects were able to key off either dimension to make a correct classification, although the redundant variation did not significantly enhance this ability. When the two variables were negatively correlated, however, this combination actually hindered classification ability. Perhaps subjects couldn't settle on which dimension to use during this classification task since either would suffice, and this switching back and forth caused problems because the two weren't correlated in a cartographically logical manner. It is also possible that low perceptibility within dimensions (component II position) played a role in subjects' abilities to choose which dimension to focus on for the classification.

Also positioned low on the configurality dimension in the PCA were shape/size, value/hue, and hue/pattern. These symbol sets exhibited poor condensation efficiency and no redundancy gains, but each had filtering interference for one of the two dimensions. In the cases of value/hue and hue/pattern, value and pattern could effectively be ignored when classifying on the basis of hue, but hue could not be ignored when classifying on the basis of value or pattern. Such results suggest that some of the graphic variables used in cartography may have more visual weight or pull than others, which shouldn't surprise those who work with or study these variables in a mapping context. It is interesting from the perspective of selective attention, however, because of what it suggests about the design of symbols with multiple graphic dimensions. This interaction of hue with value and pattern suggests that these combinations may not be the best choice if the primary goal is to produce a map where feature attributes can easily be accessed separately from one another. On the other hand, no emergent features seem to be formed from these combinations either. The lack of this type of interaction also makes the symbol a less suitable candidate for map uses that would require the user to consider the inter-relations of the data sets being symbolized. The same might be said of shape/size, where it is possible to ignore size when classifying by shape, but not vice versa.

Positioned high on the configural dimension of the PCA were the homogeneous symbol sets: value/value, pattern/pattern, hue/hue, and size/size. Of these, the ANOVAs clearly support the contention that value/value and pattern/pattern are configural. Hue/hue and size/size also seem to fit best in this category, albeit imperfectly. Both of these combinations show significant redundancy gains for correlated dimensions in one direction but not the other. This asymmetrical performance within the redundancy tasks has been noticed by other researchers (Pomerantz and Pristach, 1989). It is thought to be caused by the use of emergent properties to facilitate classification in one direction of correlation, but not the other. This is regarded as another mark of a configural interaction. These findings support the second hypothesis posed in this study.

". . . value/value and pattern/pattern are configural. Hue/hue and size/size also seem to fit best in this category, albeit imperfectly."

The remaining symbol set, orientation/length, fits none of the categories well. It exhibited poor condensation efficiency - a hallmark of separable dimensions, but not when paired with asymmetric filtering interference and redundancy gains. Apparently, one can ignore orientation to classify on the basis of length, but cannot ignore length to classify on the basis of orientation. Furthermore, there appears to be a redundancy gain for negatively correlated dimensions, but not positively correlated ones. Therefore, this symbol seems neither really separable nor completely configural.

The first two components of the PCA do not appear - on the surface, at least - to play crucial roles in determining a symbol set's level of dimensional interaction. Most symbol sets assigned to either the separable or configural dimensions varied greatly in their dimensional perceptibility (component I) and their within-dimensional variability (component II). There are a few specific instances, however, that seem to suggest these variables do play some supporting role in defining dimensional interactions. Those symbol sets that do not fall clearly into any one category of interaction are good examples of this phenomenon. The value/size symbol set, for instance, loads very low on the within-dimensional variability axis of the PCA. If these attributes of the symbol had been more distinct,

Symbol Set	Dimensional Perceptibility	Within-dimensional Variability
Configural Symbols		
Size x Size	more similar	more distinct
Hue x Hue	average	less distinct
Value x Value	less similar	average
Pattern x Pattern	less similar	less distinct
Configural Symbols		
Value x Size	more similar	less distinct
Size x Hue	average	average
Hue x Pattern	average	less distinct
Value x Shape	average	average
Value x Hue	average	average
Shape x Size	less similar	average
Shape x Hue	less similar	more distinct

Table 7. Symbol Set Characteristics

would subject performance in classification suggest a better fit for separability? Might it have changed the interaction even more dramatically? This is one area that appears to merit further exploration. At the very least, the positions of the symbol sets with respect to these components would still seem to be of interest cartographically. For instance, the most useful symbol combinations would most likely have similar perceptibilities across the dimensions used, while showing distinct within-dimensional variability. With this in mind, one should be able to use the results of this study to determine the symbol sets that match those characteristics for both separable and configural dimensions (Table 7).

CONCLUSIONS

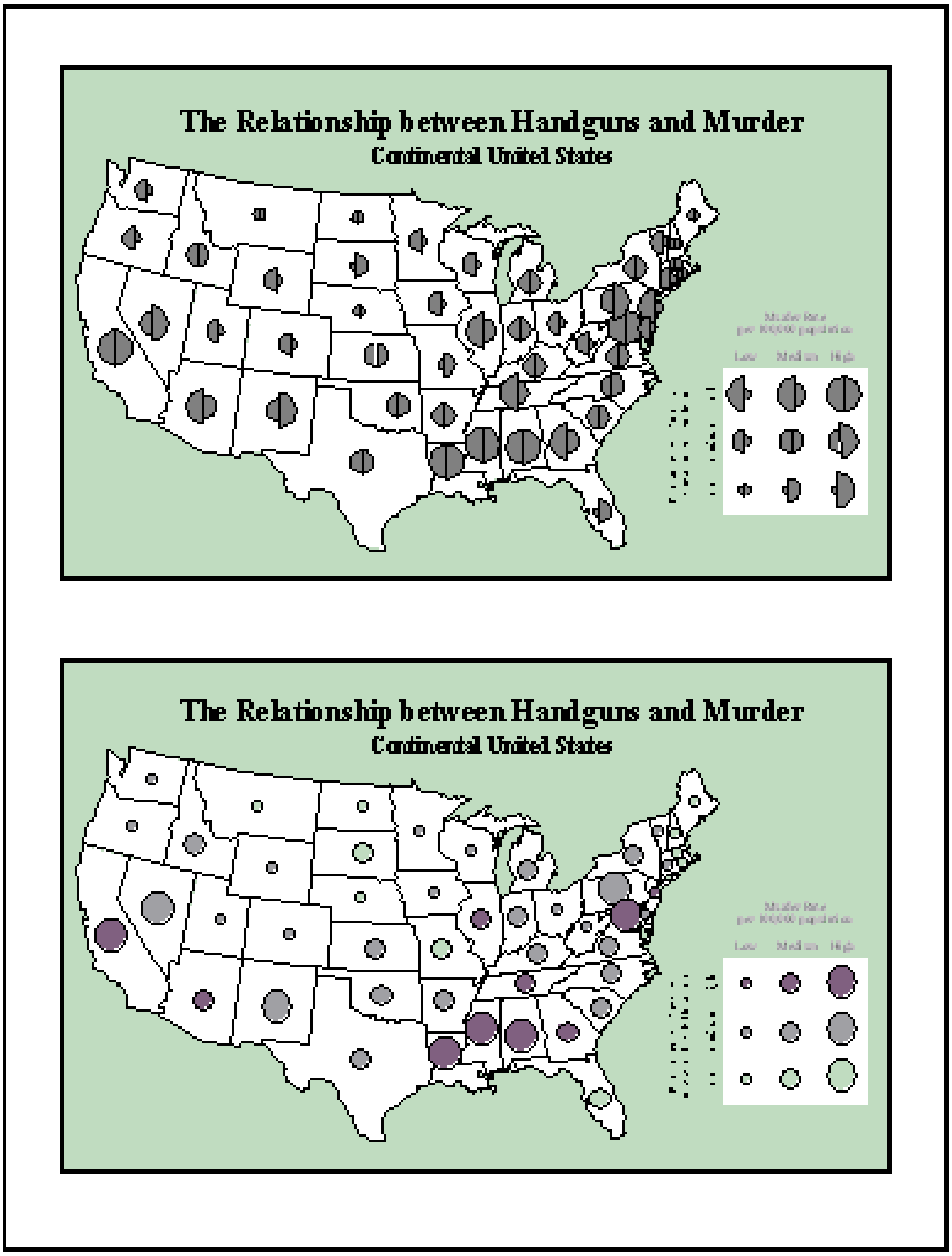

Figure 7. Two examples of how symbol designs might be used and tested in a map context.

The results of this research provide an empirical starting point for effectively choosing combinations of graphic variables for bivariate point symbol design. The data collected have confirmed some of the results published in psychological studies and have provided additional categorizations for other combinations of variables considered useful for thematic mapping. The majority of symbol sets tested in this study appear to promote either configural or separable interactions among the graphic variables comprising each set. In addition, different combinations of graphic variables appear to provide varying levels of dimensional discriminability and within-dimensional variability.

"The majority of symbol sets tested in this study appear to promote either configural or separable interactions among the graphic variables comprising each set."

Each of these factors would seem to play a role in choosing an effective method of symbolization for a bivariate map. Take, for example, a bivariate symbol needed to map a combination of two quantitative data sets with an emphasis on interpreting the distributional correlations of the data (Figure 7). Here, one might choose to use a symbol that varies size for both distributions, as this symbol set promotes a configural interaction and was also described as being above average in both dimensional perceptibility and within-dimensional variation. On the other hand, if one of the data sets was qualitative and the emphasis was on extracting spatial patterns for individual data sets, then one might choose a size/hue combination. This type of symbol promotes a separable interaction and was described as average in both dimensional perceptibility and within-dimensional variation.

The next step in this project is to confirm these findings within a map environment. This will be done by taking a subset of those symbol sets reported here and evaluating how they function within a map setting. Subjects will be asked to use the symbols to interpret mapped data, and their responses will be used to further evaluate the dimensional interactions of the symbols in question. It is also important to expand the range of graphic combinations tested to include areal, linear, and text symbols to see if the same types of relationships are at work there. A third interesting avenue of research would be to test varying levels of discriminability for combinations of graphic variables. Does the ability to discriminate graphic variables, both within and across dimensions, significantly affect their dimensional interactions?

"Further examination of selective attention, coupled with the testing of graphic variable combinations in a variety of map and non-map settings, may well lead to the development of more powerful and more understandable bivariate and multivariate maps."

Further examination of selective attention, coupled with the testing of graphic variable combinations in a variety of map and non-map settings, may well lead to the development of more powerful and more understandable bivariate and multivariate maps. On the basis of this study, the theory of selective attention appears promising as a method of guiding bivariate and multivariate symbol design.

ACKNOWLEDGMENTS

Comments on the manuscript by the anonymous reviewers are acknowledged with appreciation. A special thanks to Pat Gilmartin for her input in the early stages of this project. This research was funded by a Grant-in-Aid from San Diego State University.

REFERENCES

Attneave, F. 1962. Perception and Related Areas. In S. Koch (ed.) *Psychology: A Study of a Science*, v.4. New York: McGraw-Hill.

Barnett, B. J. and C. D. Wickens. 1988. Display Proximity in Multi-cue Information Integration: The Benefit of Boxes. *Human Factors*. 30: 15-24.

Bennett, Kevin B. and John M. Flach. 1992. Graphical Displays: Implications for Divided Attention, Focused Attention, and Problem Solving.

Human Factors. 34(5): 513-533.

Bertin, Jacques. 1983. *Semiology of Graphics: Diagrams, Networks, Maps*. Madison, Wisconsin: University of Wisconsin Press. Translated by William Berg from *Semiologie Graphique* (1967). Paris: Editions Gauthier-Villars.

Carlyle, I. P., and W. J. Carlyle.1977. The Ellipse / A Useful Cartographic Symbol. *The Canadian Cartographer*. 14(1): 45-58.

Carr, Daniel. 1991. Looking at large Data Sets Using Binned Data Plots. In A. Buja and P. Tukey (eds) *Computing Graphics in Statistics*. Spring-Verlag: 7-39.

Carr, Daniel, Anthony Olson, and Denis White. 1992. Hexagon Mosaic Maps for Display of Univariate and Bivariate Geographical Data. *Cartography and GIS*. 19(4): 228-236.

Carswell, C. M., and C. D. Wickens. 1990. The Perceptual Interaction of Graphical Attributes: Configurality, Stimulus Homogeneity, and Object Integration. *Perception and Psychophysics*. 47: 157-168.

Carswell, C. M., and C. D. Wickens. 1988. Comparative Graphics: History and Applications of Perceptual Integrality Theory and the Proximity Compatibility Hypothesis. *Technical report ARL-88-2/AHEL-88-1*. Savoy, Illinois: Aviation Research Lab, Institute of Aviation, University of Illinois.

Casey, E. J. and C. D. Wickens. 1986. Visual Display representation of Multidimensional systems. *Technical Report CPL-86-2/MDA903-83-K-0255*. Champaign, Illinois: Cognitive Psychophysiology Laboratory, University of Illinois.

Coury, B. G. and J. Purcell. 1988. The Bargraph as a Configural and Separable Display. *Proceedings of the Human Factors Society 32nd Annual Meeting*. 1361-1365. Santa Monica, California: Human Factors Society.

Dahlberg, Richard. 1981. Educational Needs and Problems within the National Cartographic System. *The American Cartographer*. 8(2): 105-114.

Dent, Borden D. 1996. *Cartography: Thematic Map Design*. Dubuque, Iowa: William C. Brown Publishers.

Dobson, Michael. 1983. Visual Information Processing and Cartographic Communication: The Utility of Redundant Stimulus Dimensions. In D. R. Fraser Taylor (ed.) *Graphic Communication and Design in Contemporary Cartography*. England: John Wiley and Sons.

Dykes, J. R. 1979. A Demonstration of Selection of Analyzers for Integral Dimensions. *Journal of Experimental Psychology: Human Perception and Performance*. 5: 734-745.

Dykes, J. R. and R. G. Cooper. 1978. An Investigation of the Perceptual Basis of Redundancy Gain and Orthogonal Interference for Integral Dimensions. *Perception and Psychophysics*. 23: 36-42.

Egeth, H. E. 1966. Parallel versus Serial Processes in Multidimensional Stimulus Discrimination. *Perception and Psychophysics*. 1: 245-252.

Felfoldy, G. L. 1974. Repetition Effects in Choice Reaction time to Multidimensional Stimuli. *Perception and Psychophysics*. 15: 453-459.

Garner, W. R. 1977. The Effect of Absolute Size on the Separability of the Dimensions of Size and Brightness. *Bulletin of the Psychonomic Society*. 9:380-382.

Garner, W. R. 1978. Selective Attention to Attributes and to Stimuli. *Journal of Experimental Psychology: General*. 107(3): 287-308.

Garner, W. R., and G. L. Felfoldy. 1970. Integrality of Stimulus Dimensions in Various Types of Information Processing. *Cognitive Psychology*. 1: 225-241.

Gottwald, R. L. and W. R. Garner. 1975. Filtering and Condensation Tasks with Integral and Separable Dimensions. *Perception and Psychophysics*. 18: 26 - 28.

Handel, S. and S. Imai. 1972. The Free Classification of Analyzable and Unanalyzable Stimuli. *Perception and Psychophysics*. 12: 108-116.

Jones, P. and C. D. Wickens. 1986. The Display of Multivariate Information: The Effects of Auto- and Cross-Correlation, display format, and reliability. *Technical Report CPL-86-5*. Champaign, Illinois: Cognitive Psychophysiology Lab, University of Illinois.

Kemler, D. G. and L. B. Smith. 1979. Accessing Similarity and Dimensional Relations: Effects of Integrality and Separability on the Discovery of Complex Concepts. *Journal of Experimental Psychology: General*. 108: 133-150.

Lockhead, G. R. and M. C. King. 1977. Classifying Integral Stimuli. *Journal of Experimental Psychology: Human Perception and Performance*. 3: 436-443.

MacEachren , Alan M. 1995. *How Maps Work: Issues in Representation, Visualization, and Design*. New York: Guilford Press:

Monahan, J. S. and G. R. Lockhead. 1977. Identification of Integral Stimuli. *Journal of Experimental Psychology: General*. 106: 94-110.

Muehrcke, Phillip and Juliana Muehrcke. 1992. *Map Use: Reading, Analysis and Interpretation*. 3rd edition. Madison, Wisconsin: JP Publications.

Nelson, E. and P. Gilmartin. 1996. An evaluation of multivariate quantitative point symbols for maps. In C. H. Wood and C. P. Keller (eds.) *Cartographic design: Theoretical and practical perspectives*. New York: John Wiley & Sons.

Pomerantz, J. R. and W. R. Garner. 1973. Stimulus Configuration in Selective Attention Tasks. *Perception and Psychophysics*. 18(5): 355-361.

Pomerantz, James R. and Edward A. Pristach. 1989. Emergent Features, Attention, and Perceptual Glue in Visual Form Perception. *Journal of Experimental Psychology: Human Perception and Performance*. 15(4): 635-649.

Rhind, D., M. A. Shaw, and R. J. Howarth. 1973. Experimental Geochemical Maps - A Case Study in Cartographic Techniques for Scientific Research. *The Cartographic Journal*. 10(2): 112-118.

Sanderson, P. M. J. M. Flach, M. A. Buttigieg, and E. J. Casey. 1989. Object Displays Do Not Always Support Better Integrated Task Performance. *Human Factors*. 31:183-198.

Schumann, B. C. and M. D. Wang. 1980. Effects of Redundancy on Speeded Classification of Integral and Nonintegral Stimuli. *Bulletin of the Psychonomic Society*. 15: 221-224.

Shepard, R. N. 1964. Attention and the Metric Structure of the Stimulus Space. *Journal of Mathematical Psychology*. 1: 54-87.

Shortridge, Barbara. 1982. Stimulus Processing Models for Psychology: Can We Use Them in Cartography? *The American Cartographer*. 9(2): 155-167.

Smith, L. B. 1980. Development and the Continuum of Dimensional Separability. *Perception and Psychophysics*. 28: 164-172.

Smith, L. B. and M. C. Kilroy. 1979. A Continuum of Dimensional Separability. *Perception and Psychophysics*. 25:285-291.

SPSS, Inc. 1997. SPSS Base 7.5 *Applications Guide*. Chicago, Illinois: SPSS, Inc.