Designing Effective Bivariate Symbols: The Influence of Perceptual Grouping Processes

By: Elisabeth S. Nelson

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Abstract:

The purpose of this research was to empirically assess perceptual groupings of various combinations of symbol dimensions (e.g., graphic variables) used in designing bivariate map symbols. Perceptual grouping ability was assessed using the theory of selective attention, a construct first proposed in psychological research. Selective attention theory contends that one's ability to analyze a symbol's dimensions—such as color or size—is affected by other dimensions present in the same symbol. Symbol dimensions 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 (i.e., show characteristics of both integrality and separability, which may also form new, emergent properties). Without empirical evidence describing such interactions for various combinations of symbol dimensions, cartographers cannot truly evaluate the functionality of the symbols they use on maps. The symbol dimensions or graphic combinations chosen for this study were selected to incorporate a wide range of traditional cartographic symbolization, including line and lettering symbolization, areal shading, dot patterns, and point symbols. Combinations were examined in an abstract setting using a speeded classification task, which is the traditional means of studying selective attention. Subject reaction times provided an assessment of the levels of integrality, separability, and configurality. Results suggest that most symbol dimension combinations are either separable or exhibit evidence of asymmetrical dimensional interactions. Findings from this study will be integrated into subsequent experiments, the results of which will assist cartographers in the design of complex map symbols.

Article:

Introduction

Mapping spatial relationships, especially when two or more data sets occur simultaneously in the same geographic space, can be a challenging task. Often there are no simple solutions, for cartographers have few firm rules upon which they can base design decisions for bivariate and multivariate symbol design. A dearth of cartographic research in this area makes it difficult for the mapmaker to knowledgeably determine combinations of graphic variables that will be most for different map emphases. For example, a combination that will effectively depict the correlation occurring between two data sets may not be optimal for a map in which the primary emphasis is to analyze the data sets individually. Bertin (1983), in his *Semiology of Graphics: Diagrams, Networks, Maps*, proposed a set of rules that describe how cartographers might best use graphic variables in conjunction with the type of data being mapped. One issue that he addressed was how the perceptual grouping of graphic variables might interact with a map reader's attention processes. 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 multivariatee spatial data.

The purpose of this research was to empirically assess the perceptual groupings or various combinations of graphic variables used in cartography. The particular combinations chosen were selected to incorporate a wide range of traditional cartographic symbolization, including line and lettering symbolization, areal shading, dot patterns, and point symbols. The results presented here represent the second in a series of four experiments.

The overarching goal of this set of experiments is to examine combinations of graphic variables for several types or bivariate map symbols, and to do this in both non-map and map settings. The data gathered in the non-map settings are intended to replicate and expand upon previous studies conducted in psychology; these results ultimately will be used to direct subsequent studies conducted in map settings. See Nelson (1999) for the results of the first experiment, which looked at combinations of graphic variables specifically for the design of bivariate point symbols.

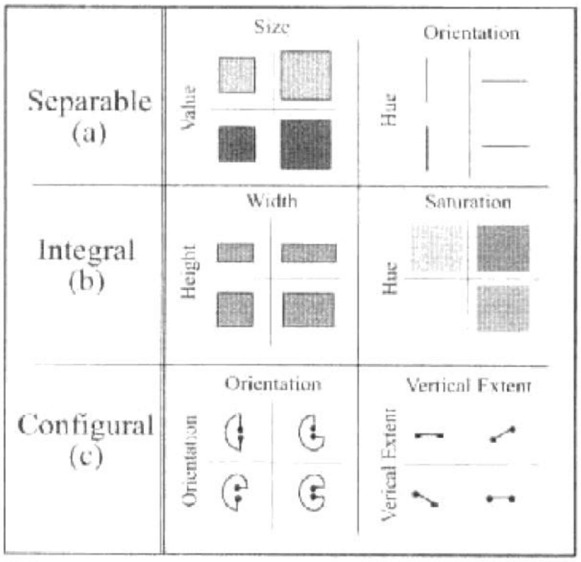


Figure 1. Examples of psychological stimuli tested using selective attention theory.

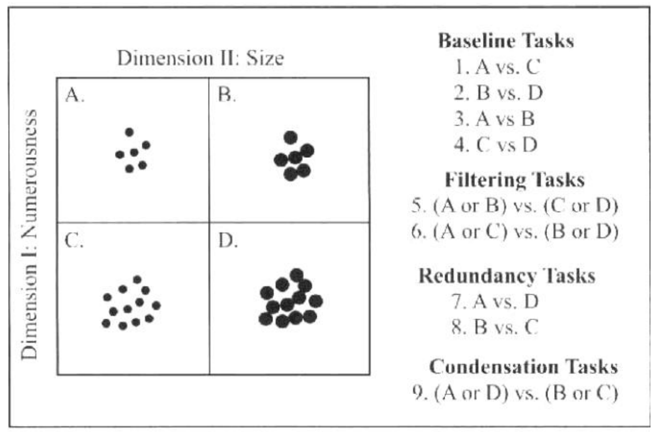


Figure 2. Speeded classification: Symbol set example and tasks. [After Carswell and Wickens 1990]

Theoretical Underpinnings: Selective Attention Theory

Psychological research emphasizes the theory of *selective attention* as a way of measuring the perceptual grouping of features in a visual image. The essence of selective attention is the ability to focus on a single dimension (or graphic variable) in a visual image, such as the size or value of a group of symbols, while ignoring all other symbol dimensions. Under this definition, symbol dimensions in which variation can be processed independently of all other dimensional variations are called *separable*. With such symbols, it is easier to focus solely on the information mapped onto one dimension, such as the size of a symbol, because information mapped onto a second dimension, perhaps value, can be effectively filtered during information processing. Studies in psychology suggest the following dimensions are separable (Figure 1a):

- Size/Value (Handel and Imai 1972; Gottwald and Garner 1975; Garner 1977; Kemler and Smith 1979; Smith 1980);
- Circle size/Angle of diameter (Garner and Felfoldy 1970; Schumann and Wang 1980);
- Tilt of a line within a form (Egeth 1966);
- Color/Orientation (Carswell and Wickens 1990); and
- Orientation of multiple lines (Carswell and Wickens 1990).

Dimensions that are highly interdependent, meaning that they cannot be attended to without processing other symbol dimensions as well, are known as *integral*. Interdependency in this instance is typically marked by such a strong interaction that the " ...unique perceptual identities of the independent dimensions arc lost" (Bennett and Flach 1992, p. 516). With such symbols, it becomes impossible to focus solely on the information mapped onto one of the dimensions; variation in both dimensions must be processed to interpret the symbol, regardless of the task being performed. The integral stimulus dimensions that have been identified (Figure 1b) include:

- Value/Chroma (Garner and Felfoldy 1970; Gottwald and Garner 1975; Kemler and Smith 1979; Smith and Kilroy 1979; Schumann and Wang 1980; Smith 1980).

- Horizontal/Vertical dot position (Garner and Felfoldy 1970; Schumann and Wang 1980);

- Height/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).

Finally those dimensions that may be processed individually, but that may also combine or interact to form an emergent, perceptual property from the original two dimensions, are called *configural.* Configurality is viewed as an intermediate level of dimensional interaction that bridges a separable/integral continuum. When two symbol dimensions are configural, one can use the emergent property of the stimulus " ...as the sole basis for the classifications, and thus the decision can be made more quickly than if each parent dimension were being processed sequentially" (Carswell and Wickens 1990, p. 158). This emergent property may be particularly useful for processing correlation between data sets. Configural interactions have been found to occur in the following instances (Figure 1c):

- Repeated use of the same dimension (Garner 1978; Carswell and Wickens 1990);

- Vertical symmetry/Parallelism (Pomerantz and Garner 1973; Pomerantz and Pristach 1989);

- Vertical extents of line graphs (Carswell and Wickens 1990); and

- Orientations of folding fans (Carswell and Wickens 1990).

The origins of selective attention theory can be traced back to the late 1950s and early 1960s (Torgerson 1958; Attneave 1962; Shepard 1964), when the *speeded-classification task* was first used to evaluate the interaction of different dimensions comprising graphic symbols. Symbols tested under the speeded classification paradigm typically consist of two graphic dimensions, each of which varies on two levels. In Figure 2, for instance, there are four symbols labeled A to D. These symbols are comprised of two graphic dimensions: numerousness and size. Each graphic dimension has one or two levels. For numerousness, the symbol may have a few dots or may have many dots comprising it. For size, the dots comprising the symbol may be small or large. The net result is a symbol set comprised of four different symbols.

In the speeded classification task, subjects are presented with these symbols one at a time and asked to classify them using one of four categories of discrimination tasks, also listed in Figure 2: baseline, littering, redundancy, or condensation. As an example, take the first baseline task listed. For this task, the subject would see a series of symbols, presented one at a time by computer, and asked to press one key if the symbol presented was symbol A and a different key if the symbol presented was symbol C. Thus, for this task, the subject is categorizing symbols on the basis of numerousness alone, establishing a baseline reaction time for that symbol dimension.

As one progresses from the baseline tasks through the filtering, redundancy, and condensation tasks, classification becomes increasingly more challenging. *Filtering* tasks, for example, assess the ability of subjects to classify all four symbols into one of two groups by using variation in only one graphic dimension. In this task, the second graphic dimension is varied randomly to assess whether or not the secondary symbol dimension will interfere with one's ability to focus on the required dimension for correct classification. If so, the two dimensions can be said to interact on some level.

Redundancy and condensation tasks are used to pinpoint the specific type of interaction occurring between two graphic dimensions, if any. Redundancy tasks arc used to assess the ability of subjects to classify symbols defined by redundantly paired dimensions. If both dimensions of the symbol are varied together, as occurs when subjects are asked to classify symbol A into one group and symbol D into another, then subjects could use either dimension to make the correct classification, or they may use both dimensions together to enhance their ability to perform this task. When this occurs, the symbol dimensions are said to interact in an integral fashion.

Condensation tasks require subjects to attend to both dimensions of the symbol to perform the classification correctly. This task is designed to highlight configural interactions. If a symbol set enhances subjects' abilities to perform this task, it is regarded as indicative of a third, emergent, perceptual property being used to facilitate classification (Carswell and Wickens 1990). For a more indepth review of the speeded classification task, see Nelson (1999).

Evidence from studies conducted in psychology suggests that selective attention is a viable concept and that various combinations of graphic variables may either facilitate or inhibit one's ability to selectively attend to the individual dimensions comprising a graphic symbol. Such findings, if they also hold true for the perception of map symbols, would be crucial to making effective bivariate symbolization choices. Symbols composed of separable graphic variables, for example, would be expected to be more effective for certain tasks than symbols composed of integral or configural graphic variables. In the separable case, for instance, symbols should be more useful when data sets need to be accessed individually on the map rather than when the goal is to highlight data correlation.

Bivariate Symbol Design In Cartography

In the cartographic literature, the theory of selective attention is just beginning to be empirically explored, although both Shortridge (1982) and MacEachren (1995) have discussed the potential relevance of the theory to map design. Related cartographic stitches that have explored bivariate symbolization tend to fall into one of three categories:

- Those that proposed designs of bivariate symbols;
- Those that investigated the merits of redundant coding (e.g., using two visual dimensions to symbolize one variable); and
- Those that examined the effectiveness of representing two variables with a single symbol.

Bivariate Symbol Designs

Several authors have used or proposed designs for bivariate symbols, but they have not tested their effectiveness (Figure3). Brewer and Campbell (1998), for example, described a variety of bivariate point symbol designs. They proposed adjacent graduated squares, adjacent graduated semi-circles, and adjacent graduated bars as useful options for comparing two data sets. They also, discussed the use of such designs as overlaid graduated squares, overlaid graduated circles, and ellipses with graduated axes for comparison purposes. For symbol designs suitable for exploring proportional relationships, the authors proposed a second set of designs, including segmented bars, segmented squares, segmented circles, and graduated wedges.

Carr (1991) and Carr et al. (1992) used bivariate ray-glyph point symbols to symbolize trends in sulfate and nitrate deposition in the eastern United States. Each symbol in this design consisted of two rays 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 the vertical symbolized the rate of increased or decreased deposition per year.

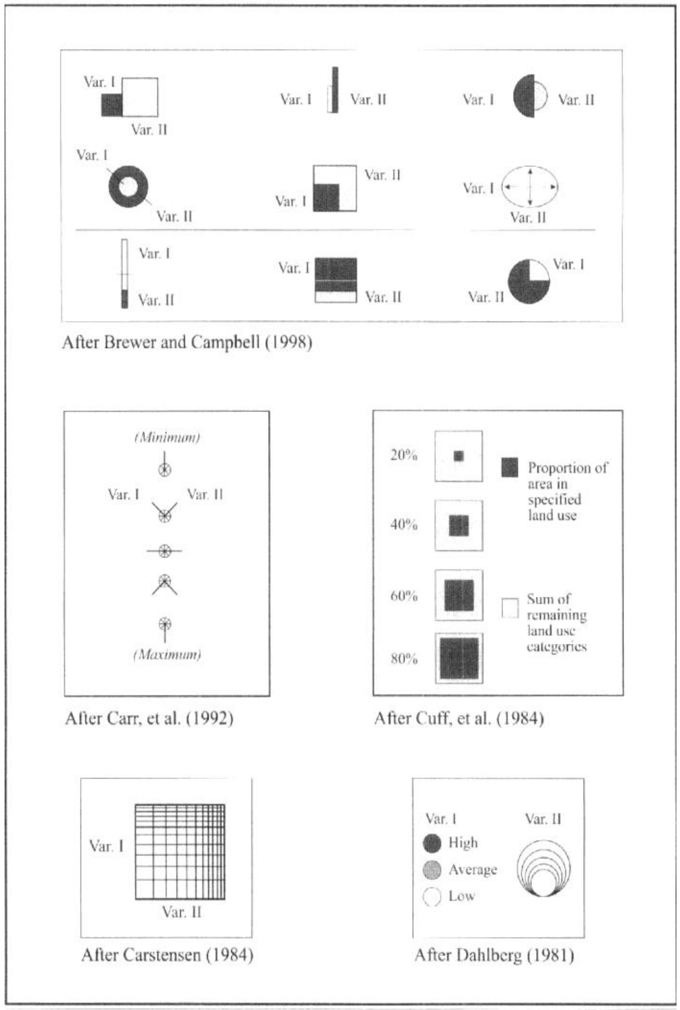


Figure 3. Bivariate symbol designs proposed or tested by cartographers.

Cuff et al. (1984) introduced the idea of nested cartograms to represent proportions of an area designated for specific land uses. In their example, they used a county map of Pennsylvania as a base map. With the standard base map remaining as a backdrop, they scaled the county areas of a second base to represent the proportion of each county's area in the predominant land use category. The area left over between the standard county size and the proportion of the county designated as the primary land use category was then shaded to represent the sum of the remaining land use categories.

As a final example, consider Dahlberg's (1981) bivariate point symbol, which combined circle size and shading value. Here, symbol size was used to illustrate the number of cartographic course offerings, while symbol value represented the relative importance of cartography programs at U.S. colleges and universities.

Redundant Coding Studies

Other cartographers have examined the idea of redundant coding in map symbolization. Lavin et al. (1986) and Amedeo and Kramer (1991), for example, represented the distribution of rainfall by combining a dot density background with an overlay of isolines. Their hypothesis was that the continuously varying background shading would convey the impression of a continuous value transition, while the isolines would communicate values at specific locations.

Dobson (1983) also investigated the utility of redundant coding, but for 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 redundant symbolization resulted in subjects responding more quickly and more accurately, 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 (1995) 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.

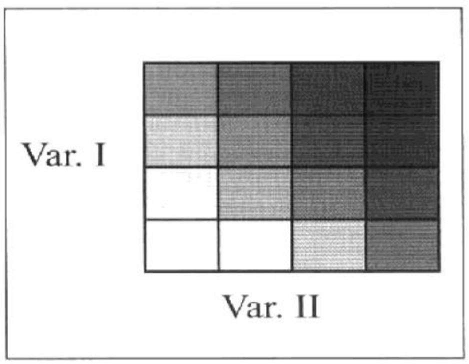


Figure 4. Example of bivariate choropleth legend. [After Olson 1981]

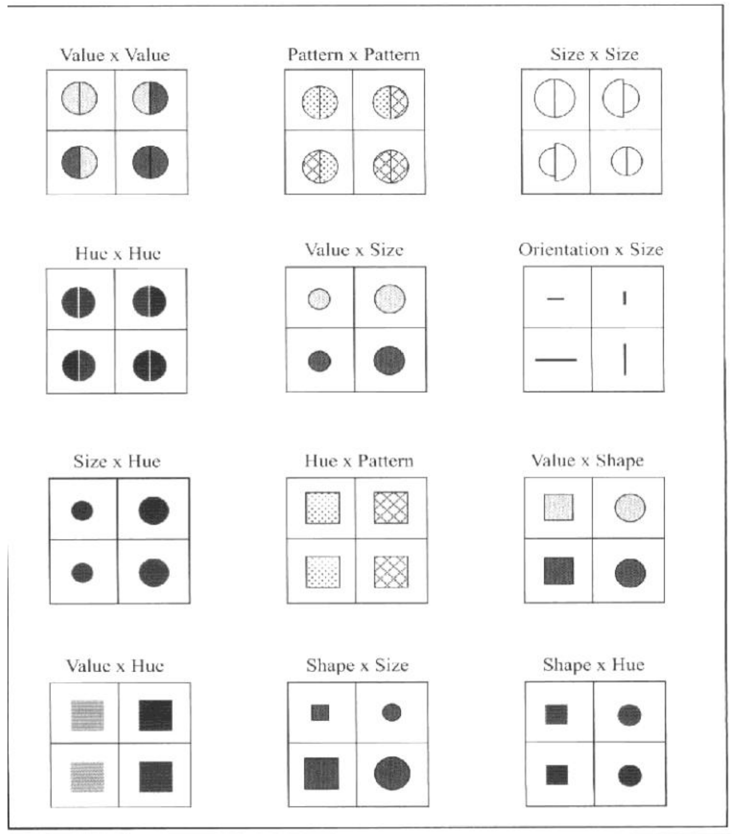


Figure 5. Bivariate point symbol designs tested by Nelson (1999).

Experimental Studies

Most efforts to test the effectiveness of bivariate symbolization have focused on choropleth map symbols. Bivariate choropleth maps consisting of variably spaced lines in crossed-line shading patterns have been studied by Lavin and Archer (1984) and Carstensen (1982, 1984, 1986a, 1986b). Lavin and Archer (1984) examined the potential of unclassed bivariate choropleth maps to serve as analytical tools. Carstensen studied a number of factors related to the perception and interpretation of bivariate choropleth maps, including subjects' abilities to make valid interpretations (Carstensen 1982); to form regions of similarity (Carstensen 1984); and to determine the validity of hypotheses (Carstensen 1986a). He has also studied the impact of scaling methods on map appearance (Carstensen 1986b). As Figure 4 shows, other authors have investigated subjects' abilities to interpret spectrally encoded bivariate choropleth maps (Olson 1981; Wainer and Francolini 1980). Along similar lines, Eyton (1984) proposed an alternative color system for bivariate choropleth maps that used pairs of complementary colors rather than the primary colors employed on the earlier spectrally encoded maps.

Slocum (1981) conducted an empirical study not on bivariate choropleth maps, but on two-sectored pie graphs. His experiments measured the just-noticeable difference for sector sizes and tested subjects' abilities to perform sector magnitude estimations. The results of his study indicated that subjects could not discriminate between sector sizes when the difference was less than 9 degrees. For the magnitude estimation experiment, he found that sector magnitudes within a 3 percent error range were estimated with 80 to 90 percent accuracy On the basis of these results, Slocum suggested rounding the data to the nearest five percent before constructing symbols.

The only study that has specifically examined the role of selective attention in the design of bivariate map symbols is Nelson. (1999). In this initial exploration, I assessed perceptual groupings for several combinations of Bertin's traditional graphic variables, with an emphasis on combinations that would be effective for bivariate point symbol design (Figure 5). Testing took place in an abstract setting, using the speeded classification paradigm. Results indicated that the majority of combinations tested promoted either separable or configural interactions, Combinations in which subjects could clearly attend to graphic dimensions separably included size/hue, value/size, value/shape, and shape/hue. Symbol sets composed of homogeneous combinations (size/ size, value/value, hue/hue), on the other hand, exhibited a strong configural interaction. In addition to these findings, several symbol sets exhibited asymmetrical effects. For these sets, I found that when certain graphic variables are paired, one of the variables tends to provide a much stronger visual cue to the subject. For example, when a symbol varies in both shape and size, it is easier for subjects to process the shape information when size is varied randomly during classification than vice versa. This indicates that, when paired with size, shape variation is a stronger visual cue and more difficult to ignore. This pattern of perceptual processing was also revealed in the hue/pattern and hue/value combinations.

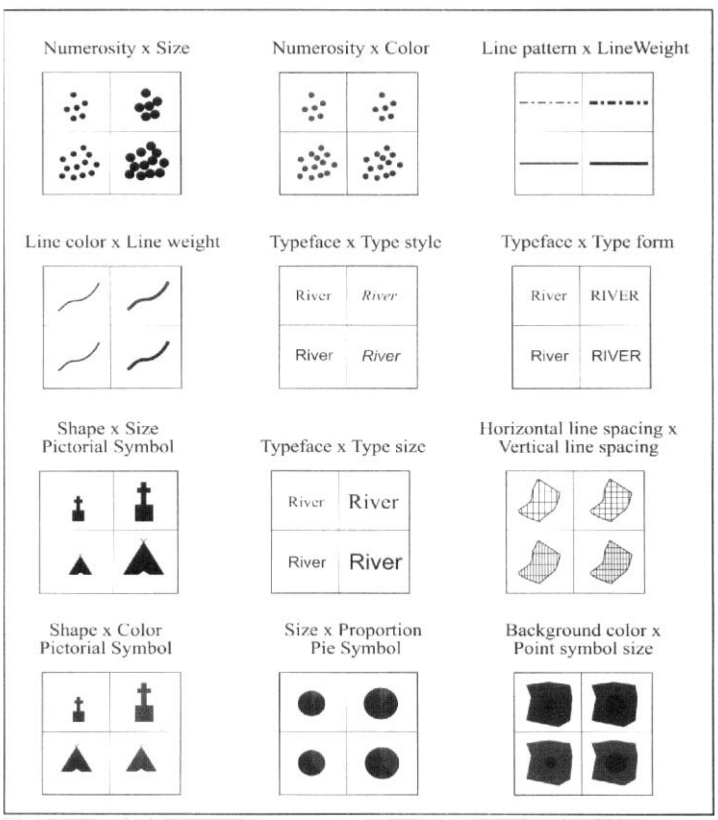


Figure 6. Bivariate symbol sets tested in this study.

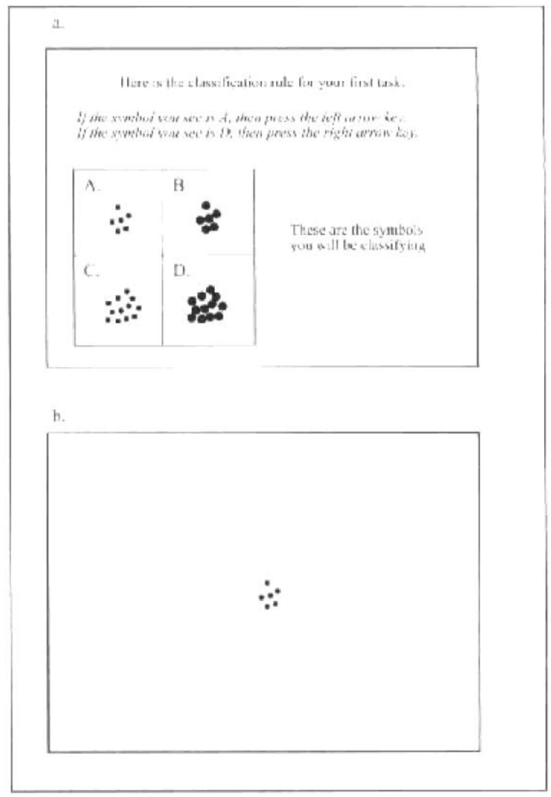


Figure 7. Experimental design: (a) Presentation of a classification rule and symbol set; (b) An actual test screen that required the subject to classify the symbol on the basis of the rule given in (a).

Experimental Design

Symbol Sets

Twelve symbol sets were tested in the present experiment (Figure 6). These sets incorporate a wide array of possible map symbols, including lettering and linear symbols, areal symbols, dot patterns, and additional examples of point symbols not covered in the first experiment (Nelson 1999). Every symbol set was composed of two graphic variables, each of which varied on two levels, resulting in four individual symbols for each symbol set. For example, in the Numerousness/Size symbol set in Figure 6, levels 1 and 2 (less and more) of dimension 1 (numerousness) are represented in the upper and lower rows of cells of the figure. Levels l and 2 (small and large) of dimension 2 (size.) are in the left and right columns of the cells.

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.

Research Hypotheses

Several research hypotheses, aimed at specific graphic combinations, were posed:

- The graphic combination of line-hue/line-size should behave as separable dimensions (Nelson 1999). For analysis purposes, this means reaction times for the baseline, filtering, and redundancy tasks should be equivalent, while those for the condensation task should show an increase relative to the reaction times for the filtering tasks.

- The graphic combination of shape/hue for pictorial point symbols should also behave as separable dimensions (Nelson 1099).

- The shape/size combination for pictorial symbols should exhibit asymmetric filtering interference, suggesting that the two dimensions arc not equal in perceptual strength when paired. It should be easier for subjects to classify symbols by size when shape varies randomly than vice versa (Nelson 1999).

- The graphic combination of horizontal/vertical dimensions since this could be considered a homogenous combination of dimensions (Garner 1978; Carswell and Wickens 1990; Nelson 1999). 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.

Subjects

Sixty subjects solicited from the student population at San Diego State University, participated in the experiment. Class announcements and posted fliers were used to attract subjects, each of which was paid %5.00 for participating. Subjects ranged from undergraduate to graduate in academic level. Thirty-five of the sixty were male, and most were geography majors, although no particular expertise in geography or cartography was required to participate in the experiment.

Test Procedure

Each subject performed nine different speeded classification tasks for four of the 12 symbol sets. 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 2. The first set of trials for each block was considered a practical trial; therefore, the corresponding data were not part of subsequent analyses. 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 testing procedure used was derived from the classic speeded classification experiment used in seminal psychological studies. The basic procedure was automated for this study by coding necessary sequence of events using Visual Basic on Windows/NT operating system. Following the initial instructions of the experimenter, which outlined the central idea and methodology of the experiment, the Visual Basic 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 redundancy tasks, the subject might have been instructed to press the left arrow key if the presented symbol was A, and to press the right arrow key if the presented symbol was D (Figure 7a). The symbols for the block of trials were then presented on-screen one at a time in a random order (Figure 7b). Each symbol remained onscreen 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: (1) the percentage of classifications they completed correctly, and (2) their mean correct response time. When then nine blocks were completed for a given symbol set, subjects were allowed to take a short break before beginning the test for the nest set of symbols. Reaction times for each symbol set were recorded for analysis. See Figure 8 a-d for examples of classification screens for each category of discrimination tasks.

Task Comparison[a]	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 $RT_{(T9)}$	•[b]	•[c]	

[a] T1 – Task 1; T2 – Task 2, etc.
[b] T9 has significantly longer response times.
[c] T9 has significantly shorter response times.

Table 1. Planned comparisons: Analysis of variance.

Results and Discussion

Reaction time data for each symbol set were subjected to an analysis of variance to evaluate the prevalence of separable, integral, and configural interactions for the combinations of graphic variables comprising each symbol set. Prior to theses analyses, the data were manipulated to eliminate incorrect responses and extreme values, as defined using the method of Tukey's Hinges (SPSS, 1997). Because the remaining data were skewed for each symbol set, geometric means were computed for all subject responses within each category. Reaction time served as the dependent variable in separate analyses for each symbol set. The independent variable in each case was task (nine levels). 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).

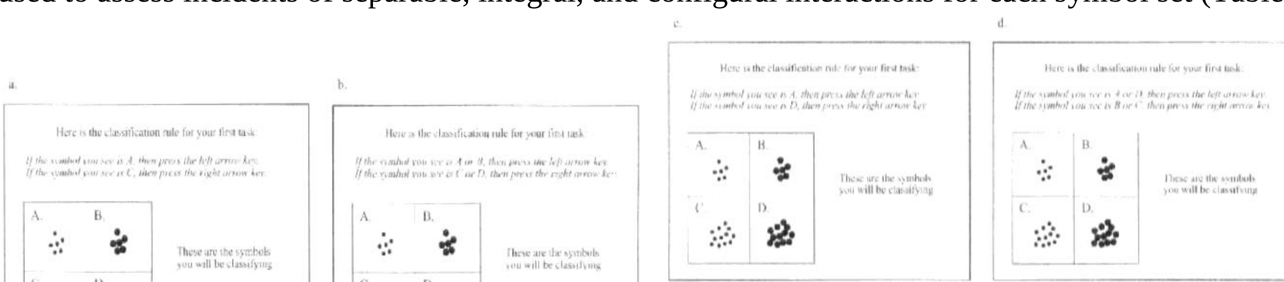


Figure 8. Examples of classification screens for each task category: (a) Baseline classification; (b) Filtering classification; (c) Redundancy classification; (d) condensation classification.

Combinations of graphic variables are considered separable when they clearly do not interact during the perceptual processing of the symbol they comprise. From an analytical standpoint, this means reaction times for baseline tasks do not differ significantly from reaction times for filtering tasks, where variation in the second dimension is varied randomly during classification. Nor do they differ significantly from response times for redundancy tasks, where both dimensions are varied simultaneously during classification. Furthermore, with no interaction occurring between dimensions, reaction times for the condensation tasks should increase significantly relative to filtering task responses, since variation in both dimensions must be processed simultaneously to perform this task efficiently. Of the 12 symbol sets tested in this study, three meet these criteria stringently: line-hue/line-size, pie-size/pie-proportion, and numerousness/hue (Figure 9; Table 2). These combinations, then, would appear to be useful for mapping data in which it is more important to be able to access data sets individually than it is to efficiently process data correlation. Such a need might occur when multiple data sets are mapped together due to space or economic considerations.

		Line Hue (D1)/ Line Size (D2)*	Pie Size (D1)/ Pie Proportion (D2)	Numerousness (D1)/ Hue (D2)
Analysis of Filtering Interference	Base RT (D1)	324	340	347
	Filter RT	327	351	365
	Significance	**0.999**	**0.698**	**0.286**
	Base RT (D2)	358	358	314
	Filter RT	358	369	321
	Significance	**1.000**	**0.732**	**0.996**
Analysis of Redundancy Gains	Fastest Base RT	324	340	314
	Positive Redundancy RT	321	334	317
	Significance	**0.998**	**0.876**	**0.998**
	Fastest Base RT	324	340	314
	Negative Redundancy RT	330	358	314
	Significance	**0.903**	**0.213**	**1.000**
Analysis of Condensation Efficiency	Mean Filter RT	380	324	340
	Condensation RT	545	508	528
	Significance	**0.000**	**0.000**	**0.000**

*D1 = Dimension 1; D2 = Dimension 2.

Table 2. Analysis results for separable symbol sets.

When reaction times for filtering tasks take significantly longer than reaction times for corresponding baseline tasks, *filtering interference,* which is indicative of some form of dimensional interaction, is said to occur. Only two symbol sets — pictorial shape/size and horizontal/vertical line spacings — showed significant evidence of filtering interference for both symbol dimensions (Figure 10; Table 3). While expected for horizontal/vertical line spacings, this was not hypothesized for the pictorial shape/size symbol set. Nelson (1999) had found *asymmetric filtering interference* for shape/size when paired in a geometric symbol set, suggesting that subjects could effectively ignore size when asked to classify symbols by shape, but not vice versa. Perhaps the added complexity associated with pictorial symbols makes shape more difficult to ignore during classification.

For the interactions suggested by the filtering tasks to be classified specifically as either integral or configural, subject responses redundancy and condensation tasks must also be considered. Integral behavior requires that reaction times for redundancy tasks be significantly shorter than reaction times for corresponding baseline tasks, indicating that the pairing of dimensional variation is enhancing classification ability. As Figure 10 shows, neither of these symbol sets exhibited this pattern. The lack of integral interactions is interesting, but not necessarily disturbing. Although several psychological studies have reported finding integral dimensions in their speeded classification testing, researchers are now questioning those results (Casey and Wickens 1986; Jones and Wickens 1986; Carswell and Wickens 1988; Carswell and Wickens 1990). 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 be more configural than integral. In these cases, a third, emergent property is believed to provide subjects with a visual shortcut that enhances the processing of correlational information when such tasks are required (Barnett and Wickens 1988; Coury and Purcell 1988; Sanderson et al. 1989).

Interactions classified as configural are marked by baseline reaction times that are not significantly different from responses for redundancy tasks and the reaction times of condensation tasks which are significantly shorter than responses for corresponding filtering tasks. As with integral behavior, however, neither the pictorial shape/size nor the horizontal/vertical line spacings revealed evidence of strong configural interactions (Figure 10). Since neither set conforms to strong integral or configural behaviors, it must be assumed that the combinations result in interactions that lie somewhere between these two definitions. Previous research lends credence to this, as it has been shown that strong configural interactions are typically associated only with homogeneous dimensions (Carswell and Wickens 1990; Nelson 1999). I had hypothesized that the horizontal/vertical spacings would be perceived as homogeneous dimensions since both dimensions varied line spacing to create the symbol set. It appears, however, that the horizontal and vertical characteristics of the spaced lines do not interact in such a way as to form the necessary perceptual property that enhances classification of data correlation.

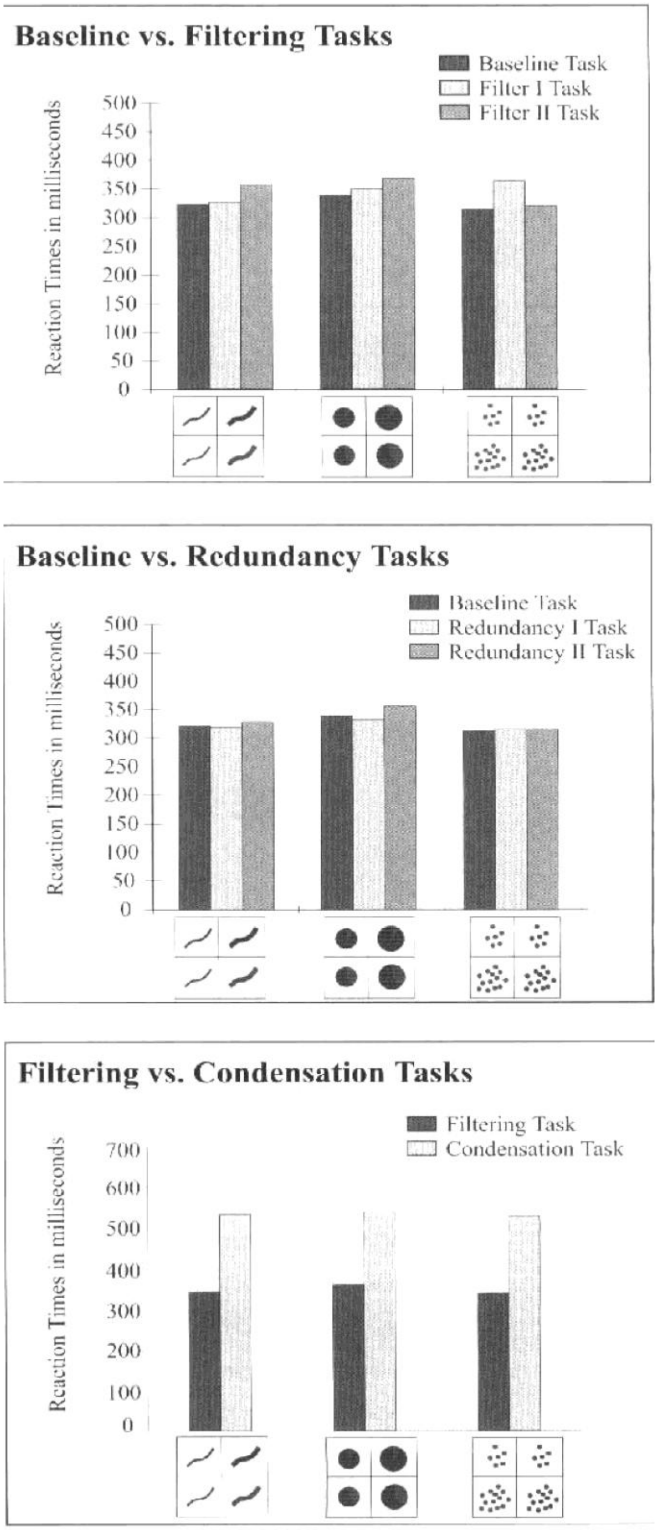


Figure 9. Separable symbol sets.

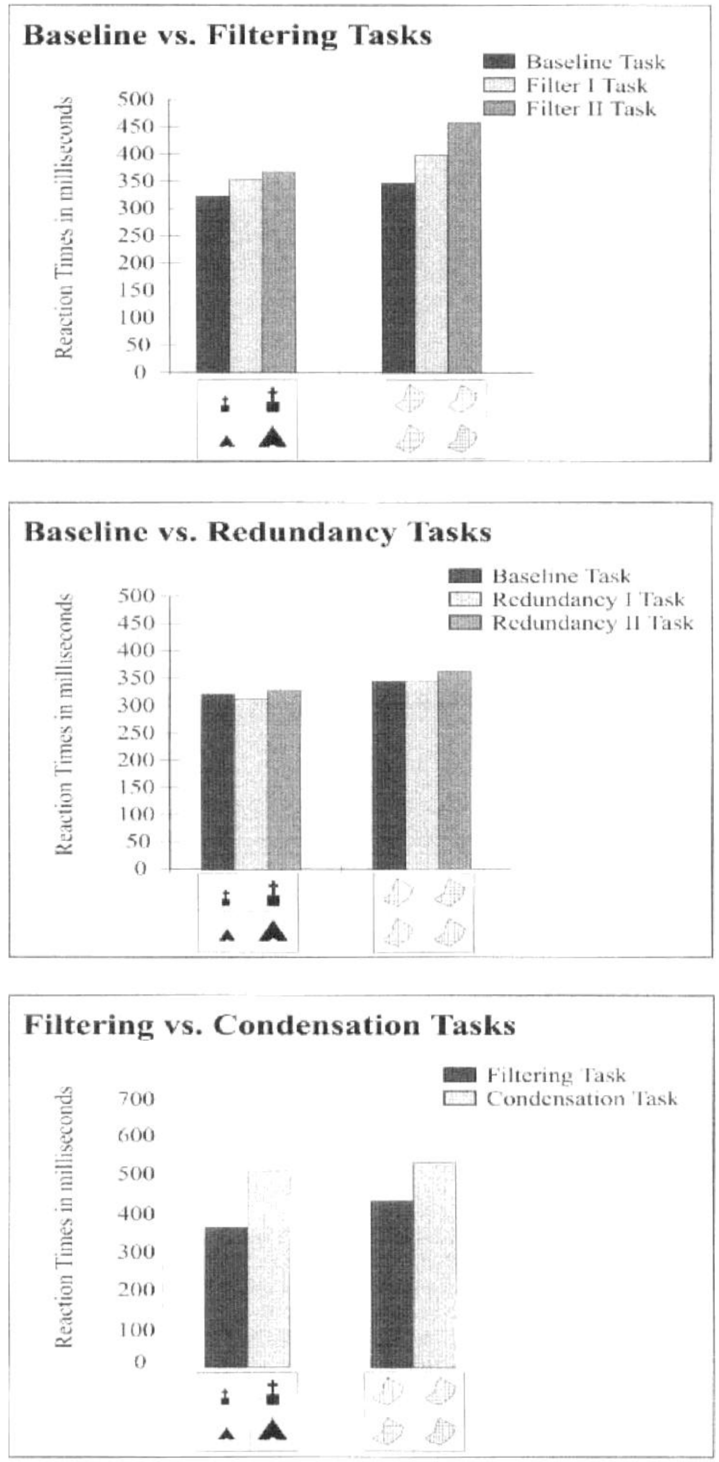


Figure 10. Symbol sets with dimensions that interact but that cannot be classified as either integral or configural using speeded classification rules.

		Pictorial Shape (D1)/ Pictorial Size (D2)*	Horizontal Line Spacings (D1)/ Vertical Line Spacings (D2)
Analysis of Filtering Interference	Base RT (D1)	324	347
	Filter RT	354	399
	Significance	0.000	0.000
	Base RT (D2)	344	399
	Filter RT	372	459
	Significance	0.002	0.000
Analysis of Redundancy Gains	Fastest Base RT	324	347
	Positive Redundancy RT	314	347
	Significance	0.860	1.000
	Fastest Base RT	324	347
	Negative Redundancy RT	330	361
	Significance	0.990	0.373
Analysis of Condensation Efficiency	Mean Filter RT	428	428
	Condensation RT	607	545
	Significance**	0.000	0.000

*D1 = Dimension 1; D2 = Dimension 2.
**Configural interactions require a significant decrease in reaction times forcondensation RTs relative to mean filter RTs.

Table 3. Analysis results for symbol sets that exhibit significant filtering interference for both symbol dimensions.

The remaining symbol sets tested did not fit neatly into any one category of interaction, Several, however, did reveal evidence of asymmetric filtering interference (Figure 11; Table 4). Symbols defined by a numerousness/ size combination, for example, exhibited reaction times suggesting that subjects could effectively ignore differences in numerousness when asked to classily symbols on the basis of size. They apparently could not, however, ignore size when asked to classify symbols on the basis of numerousness. Similar patterns were also found in:

- Line-pattern/Line-size -- could ignore size when classifying by pattern but not vice versa.
- Typeface/Type-style -- could ignore typeface when classifying by style but not vice versa.
- Typeface/Type-form -- could ignore typeface when classifying by form but not vice versa.
- Typeface/Type-size -- could ignore typeface when classifying by size but not vice versa.

		Numerousness (D1)/ Size (D2)*	Line Pattern (D1)/ Line Size (D2)	Typeface (D1)/ Type Style (D2)	Typeface (D1)/ Type Form (D2)	Typeface (D1)/ Type Size (D2)
Analysis of Filtering Interference	Base RT (D1)	395	344	395	424	412
	Filter RT	424	354	450	483	478
	Significance	0.000	0.878	0.000	0.000	0.000
	Base RT (D2)	395	365	403	388	372
	Filter RT	372	403	420	392	384
	Significance	0.567	0.000	0.362	0.993	0.579

Table 4. Filtering interference results for symbol sets with asymmetrical interactions.

Symbol/Data Types	Graphic Combinations and Interactions: Separable	Configural	Integral*	Asymmetrical**
Point				
Qualitative/Qualitative	Shape/Hue	Pattern/Pattern		Hue/Pattern
		Hue/Hue		
	Hue/Orientation**			
Qualitative/Quantitative	Hue/Size	Pattern/Pattern	Saturation/Value	Shape/Size
	Shape/Value			Hue/Pattern
				Hue/Value
Quantitative/Quantitative	Value/Size	Value/Value	Height/Width (Rectangle)	
	Pie Size/Proportion	Pattern/Pattern	Length/Length (Bars)	
		Size/Size		
Line				
Qualitative/Qualitative				
Qualitative/Quantitative	Hue/Size			Pattern/Size
Quantitative/Quantitative				Pattern/Size
Area				
Qualitative/Qualitative				
Qualitative/Quantitative	Hue/Numerousness			
Quantitative/Quantitative				Size/Numerousness

*Results from psychological studies.
**Dominant variable listed first.

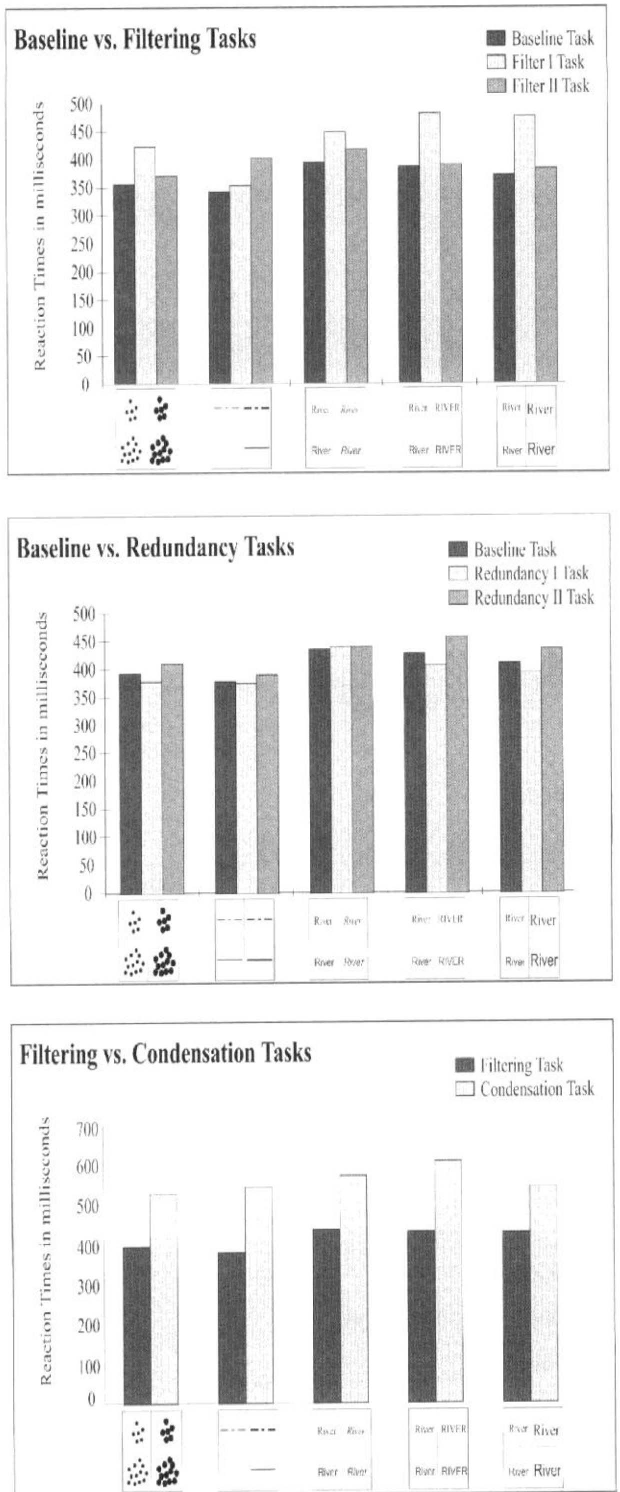
Table 5. Tested graphic combinations: Symbol types, data types, and interactions.

One possible interpretation of the asymmetric filtering interference is that the two dimensions, at least when paired in it symbol, vary in visual cue strength. If so, perhaps an effective use of these types of combinations lies in the production of maps where spatial information is presented using multiple resolutions. For example, when mapping a linear feature such as a stream, one might use line pattern to designate differences in stream flow (e.g., intermittent versus perennial streams), then use line size to provide secondary detail about stream order. In a case such as this, the average map reader might not be concerned with stream order and would choose to focus on stream flow. Stream order information, however, would still be embedded in the map for those readers interested in the additional, more specific information.

Combinations of typeface with size, form, or style present a different problem, however, under this scenario. Typically, typeface is used to denote a broad level of categorization, say that of physical versus cultural features on a map. Size, style, and form are then used to add secondary detail within each of those categories related, perhaps, to the size or importance of a given feature. Thus, it becomes more difficult to conceive of a combination in which size, style or form represent the broader category with typeface delineating differences in secondary characteristics. Perhaps it is more important here to recognize that typeface variations may be too subtle for most to discern their differences, and that other attributes of type might be better paired for bivariate representations.

Another scenario is that the asymmetric filtering interference seen here is related less to the idea that one dimension is more visually prominent than another and more to the idea that selected differences within each dimension are not perceptually equivalent. Great care was taken in selecting dimensional variation for each symbol set and several people with cartographic expertise asked to review those differences prior to testing. No objective testing, however, was done to specify differences numerically or to compare objectively the equivalency of differences between dimensions for any given symbol set. This is a step that should be incorporated into future research to provide a liner degree of calibration to such studies.

Figure 11. Symbol sets exhibiting asymmetrical interactions.



Conclusions

The results of this research add to the empirical findings from an earlier experiment (Nelson 1999) and provide a foundation from which a typology of graphic combinations can begin to be built. Table 5 represents a start in that direction, using these findings and those considered useful for mapping that have come from previously published psychological studies. The typology considers the symbol type being mapped, the types of data being mapped, and the resulting symbol interaction that might be expected when using different graphic combinations to represent the different types of data. Graphic combinations have been matched to data type combinations using standard cartographic conventions.

Each of the variables mentioned above would seem to play a role in choosing an effective method of symbolization for a bivariate map. Take, for example, the challenge of showing a combination two quantitative point data sets, in which the intention is to emphasize the correlation between the two data sets. Here, one might choose a point symbol that varies size for both distributions (Figure 12a), as this symbol promoted a configural interaction that should prove useful for enhancing data correlation (Nelson 1999). On the other hand, if one data set is qualitative and the other quantitative and the emphasis is on extracting spatial patterns for individual data sets using areal symbolization, then a different symbol is necessary. A numerousness/hue combination might be an effective choice here (Figure 12b), as this combination was shown to promote a separable interaction. For maps that are designed to display varying levels of detail for spatial data, a graphic combination that results in asvmmetrical interactions might be especially useful. A classic example here would be a map of world climatic regions. These maps often employ hue and pattern in an areal symbolization scheme, where hue is the primary variable highlighting major distinctions in climatic regions and pattern is a secondary variable providing more detailed categorizations within each hue region.

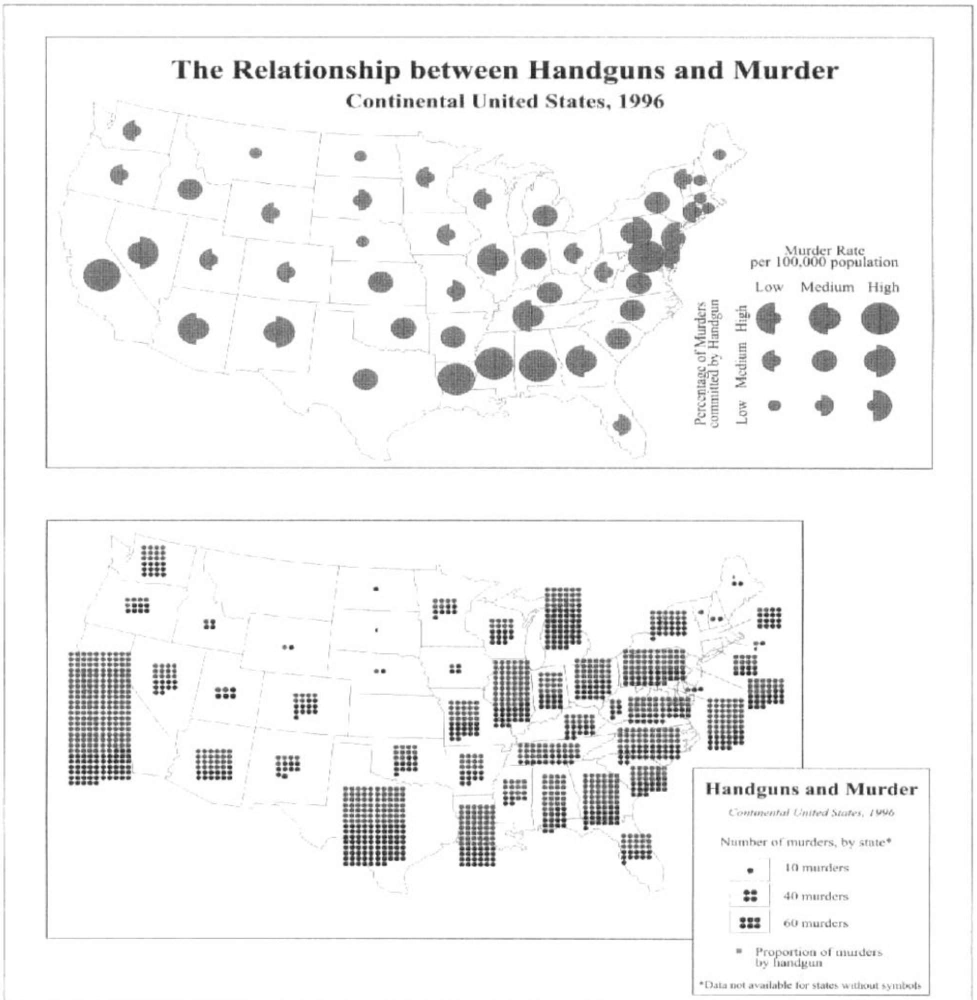


Figure 12. Examples of how symbols might be used and tested in a map context.

The next step in this project is, of course, to confirm these findings within a map environment. This will be done by taking a subset of the 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. Further examination of selective attention, coupled with the testing of graphic variable combinations in a variety of map settings, should strengthen and expand the typology presented here. It is hoped that such research ultimately will lead to more effective and understandable bivariate and multivariate maps.

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