Visual Search Processes and the Multivariate Point Symbol.

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*****Note: Footnotes and endnotes indicated with parentheses**

Abstract:

This study reviews the major theories of visual search processes and applies some of their concepts to searching for multivariate point symbols in a map environment. The act of searching a map for information is a primary activity undertaken during map-reading. The complexity of this process will vary, of course, with symbol design and map content. Multivariate symbols, for example, will be more difficult to search for efficiently than univariate symbols. The purpose of this research was to examine the cognitive processes used by map readers when searching for multivariate point symbols on a map. The experiment used Chernoff Faces as the test symbol, and a symbol-detection task to assess how accurately and how efficiently target symbols composed of different combinations of facial features could be detected. Of particular interest was assessing the role that different combinations of symbol dimensions and different combinations of symbol parts played in moderating search efficiency. Subject reaction times and error rates were used to evaluate the efficiency of the searches. Results suggested all searches employed serial search processes, although feature searches (those in which a target symbol consists of a unique feature) were by far the easiest for subjects to complete. It was also demonstrated that hierarchical relationships could be manipulated within symbols to increase search efficiency for searches in which the target does not have a unique feature (conjunctive search).

Article:

INTRODUCTION

Visual search is a fundamental activity undertaken during map-reading (Lloyd 1997; Shortridge 1982). Locating a capital city on a road map, for instance, is a classic example of this process as it relates to the map environment. Such activity requires a dynamic interaction between the map and the map reader (Dobson 1985). The cognitive processes used during this interaction to successfully complete the task are important. As MacEachren (1995,8) argues, cartographers can "... facilitate map use by developing models of human-map interaction and human spatial cognition ..." and then use these models to "... identify and more completely understand the most important variables of map symbolization and design."

The complexity of the search process, as a map-reading activity, will vary from map to map. As symbolization grows more complex and map content increases, the task of searching for information will undoubtedly become more difficult. A map that uses multivariate symbols, for example, will be more difficult to search efficiently than one using univariate symbols. Interest in multivariate symbolization has picked up considerably in the past two decades, though, thanks to an increase in computer mapping and GIS applications. Although researchers in several disciplines have designed and used multivariate point symbols, there has been little empirical research to test their effectiveness, particularly on a map. How well do multivariate symbols work, for example, in the context of searching a map for information? Are some combinations of symbol dimensions or some combinations of symbol parts located more quickly and/or more accurately than others?

PURPOSE

The purpose of this study was to examine the visual search processes used by map readers when interacting with multivariate point symbols in a map environment. Knowledge of how visual search occurs on maps composed of multivariate symbols is crucial to understanding how such symbols are perceived. With an increased understanding of these types of process, it should become possible to create more effective map symbols. The map-reading task used to evaluate search processes in this study was a symbol-detection task. In this type of task, a target map symbol is located on a map among other symbols that may or may not share characteristics with the target. Assessment of the processes used to locate target symbols should provide insight into the types of combination--both for symbol dimensions as well as symbol parts--that are found most quickly and most accurately by map users.

As noted by many others, thematic maps must typically serve a variety of functions, ranging from static storing of spatial information to facilitating complex analyses. With multivariate maps, processes can become even more complicated. Ideally, map readers should be able to retrieve information separably, focusing on some subset of data values encoded onto the multivariate symbol, as well as interpreting the symbols in a holistic or integral manner. This study speaks specifically to the design of such symbols from the perspective of retrieving information separably.

Chernoff Faces were the symbols selected as the case study for this research (Chernoff 1973). Although they have received mixed reviews across disciplines regarding their usefulness, Chernoff Faces are perhaps the best-known and most frequently used multivariate point symbols designed (Chernoff 1973; 1978; Jacobs, et al. 1976; Huff and Black 1978; Schmid 1984; Carswell and Wickens 1988; Nelson and Gilmartin 1996). Cartographic research also suggests that they may be particularly useful for displaying multiple variables that are meant to be retrieved separably (Nelson and Gilmartin 1996).These symbols can represent up to eighteen different variables by manipulating such facial features as the orientation of the mouth or the size or shape of the head. By assessing the effectiveness of combinations of symbol parts and symbol dimensions, cartographers should be able to obtain useful information about symbol design that can serve as a foundation for creating more effective multivariate maps.

CARTOGRAPHIC RESEARCH AND MULTIVARIATE SYMBOLS

Cartographers have largely ignored the empirical testing of multivariate symbol designs, especially for point symbols (MacEachren 1995). Instead, the research that does exist in this area seems to have centered on symbolization techniques for choropleth maps,((1)) who conducted a review of this literature, drew the following conclusion about the utility of these designs:

> The future of multi-component maps ultimately depends upon their reception by the map reader. There is an urgent need to study the communicative effectiveness of multi-component maps from the standpoints of researchers and the general audience.

What studies have been conducted on multivariate point symbols in cartography have generally focused on the design of such symbols at the expense of evaluating their usefulness.

Carlyle and Carlyle (1977), for example, designed an ellipse symbol that could represent three variables. They used the lengths of the semi-major and semi-minor axes to represent two variables, with the third variable being symbolized by a pie-graph representation within the ellipse. Bertin (1983) also explored the symbolization of multivariate data for point symbols by devising a symbol that varied in size, value, shape, and orientation. Bivariate ray-glyph symbols that used line direction as well as the angle created by two lines to represent multiple variables have also been designed and used on maps (Carr 1991; Carr, et al. 1992). Another example of bivariate point-symbol design is Dahlberg's (1981), which varied circle size and shading value to represent two variables in a graduated symbol context. In yet other studies, researchers have used Chernoff Faces to symbolize data with multiple components. Turner, for example, used them to symbolize four socio-economic variables in Los Angeles (reproduced in Muehrcke and Muehrcke 1992, 162). Wainer (1979) explored their potential by using them to symbolize nine quality-of-life variables for the United States.

Only two cartographic studies were found in which researchers empirically evaluated the effectiveness of quantitative multivariate point symbols. Rhind, et al. (1973) tested the effectiveness of a three-arm wind-rose type of symbol for summarizing geochemical data. The length of each arm represented a variable, as did the symbols' locations on the map. Using maps that varied both in scale and level of background noise, subjects performed several counting and estimations tasks that required interpretation of these symbols. Results indicated that subjects performed poorly under all conditions and that none of the experimental variables had much effect. Not surprisingly, the authors stated the need for additional research on the design and perception of multivariate point symbols.

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 such 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 such symbols than on their composite image. The opposite held true for the geometric symbols tested.

MODELLING VISUAL SEARCH PROCESSES

Cartographers have not thoroughly examined the processes map readers use in searching for multivariate point symbols, but such research has the potential to offer useful insights into effective symbol design to those who make maps. The standard task used by psychologists to measure search efficiency is one in which subjects search for a specific target item among a field of distractor items. Targets can be defined by a single feature (e.g., size or colour), a conjunction of features such as some combination of colour and shape, or a variety of other complex properties (Wolfe 1994). The number of distractor items varies across experimental trials, and the researcher records subjects' reaction times and accuracy rates for each trial.

Variation in reaction time as a function of the number of distractors is then used to make inferences about the underlying structure of the visual-search process (Wolfe 1994). For example, when reaction times are dependent on the number of distractors present, this indicates that subjects must focus on each item in the visual field to assess target presence or absence. Since each item must be attended to individually, the search is termed a serial process. When reaction times are independent of the number of distractors present, the search is considered a parallel process because subjects determine target presence or absence without focusing on individual items in the visual field (Treisman 1988).

Another factor used to assess search processes is the slope of the search function. Search slopes describe the change in reaction time as a function of the number of distractors in the visual field. If a search slope is significantly different from zero, then the search is considered a serial search. Typically, such searches have slopes greater than 20 ms/item (Duncan and Humphreys 1989). A search slope that is near zero (usually less than 6 ms/item), suggests a parallel search.

Comparing target-present searches with target-absent searches is also constructive. In a serial self-terminating search, target-absent searches require consideration of all potential target locations before making a decision about target absence. Target-present searches, on the other hand, usually require searching approximately one-half the locations before determining that the target is present. A comparison of slopes for target-absent versus target present-searches, then, should yield about a 2:1 ratio for serial self-terminating searches (Treisman and Gelade 1980). Examining the search processes in this way has led psychologists to propose a number of models that outline the various stages of the visual-search process. Two of these models are briefly summarized below.

Feature Integration Theory

A central idea in early visual-search models is that visual processing occurs in two stages (Neisser 1967). The first stage is pre-attentive, with initial processing occurring in parallel across the visual field. The second stage is attentional, with attention being restricted to local areas within the visual field. This idea forms the foundation of Feature Integration Theory, one of the seminal visual-search models (Treisman and Gelade 1980; Treisman 1986; 1988).

Feature Integration Theory proposes that the human visual system first perceives the elementary attributes of a scene, such as colour and shape. Perception of such dimensions occurs in parallel across the visual field, yielding a number of feature maps, each of which represents one feature of a dimension (e.g., if the dimension is colour, then a feature might be red or blue). When the target consists of a unique feature, the feature maps allow target detection to occur automatically and without focused attention (Treisman and Gelade 1980; Treisman 1988). For example, if the target is a red triangle in a field of yellow triangles, the feature map of redness allows the perceiver to detect the target without focused attention. However, when the perceiver must locate and conjoin features from different feature maps to specify an object, then attention-the glue that integrates separate features into objects--is required to complete the task. Thus, if the target is a red square located in a field of red circles and yellow squares, then the perceiver must conjoin the feature maps of redness and squareness to detect the target item. When this type of conjoining occurs, searching becomes a serial process. Since the initial proposal of this model, several researchers have produced data that do not fit neatly into its original framework (Egeth, et al. 1984; Nakayama and Silverman 1986a, 1986b; Wolfe, et al. 1989; 1990; Treisman and Sato 1990). Feature Integration Theory has thus been modified over time to account for serial feature searches caused by the similarity of targets and distractors (Treisman and Gormican 1988) and parallel conjunctive searches caused by highly discernible targets and distractors (Treisman 1988).

Guided Search Model

Cave and Wolfe's Guided Search Model (1990) is a modification of Feature Integration Theory and also the model upon which this study draws. Under this model, Feature Integration Theory's two stages of visual processing are retained, but are not considered completely independent of one another. Rather, researchers suggest that the parallel stage of search guides the subsequent serial stage, allowing conjunctive searches to result in parallel search times under certain conditions (Wolf, et al. 1989; Wolf, et al. 1990).

Under the Guided Search Model, target detection begins by using the parallel stage of processing to identify the most likely candidates in the visual field. Like Feature Integration Theory, this model proposes that separate feature maps are produced for each dimensional feature found in the visual field. Each location on each feature map is assigned an activation value describing the likelihood of that location holding the target. These activation values are composed of both bottom-up and top-down information (Cave and Wolfe 1990; Wolfe, et al. 1990). The difference between the feature value at the potential target location and the feature value at every other location in the visual field comprises the bottom-up component. For example, the search for a unique target among homogenous distractors leads to very strong bottom-up activation because the distractors are all alike, which makes the target, in effect, 'pop-out.' Top-down information also contributes to search efficiency, but consists of the similarity between the potential target location and the known properties of the target. Feature values for each location are then summed across the feature maps, yielding an activation map in which the values for each location describe the likelihood of the target existing there. This information is then passed to the serial processing stage, which determines whether the target is present or absent in the visual field.

Because it is the parallel stage of processing that combines information from all the feature maps, it should, theoretically, be possible to find conjunctive targets as easily as feature targets. What prevents this from happening, however, is a noise component in the system that causes search times to vary. If the level of noise is low, the serial processing stage will find the target quickly and search times will indicate that the perceiver used a parallel search process. If, however, the noise level is high, the serial stage may have to process many potential locations before the perceiver locates the actual target. This would lead to serial search times (Wolfe, et al. 1990; Cave and Wolfe 1990).

One of the earlier studies that supported this theory examined search behaviour for conjunctions of colour and form (Wolfe, et al. 1989). Subjects searched for a green X among a field of green Os and red Xs. Results suggested that reaction times were comparable to those Treisman and Gelade (1980) obtained for feature searches, indicating that the parallel stage was guiding the serial stage and producing parallel search times for conjunctive searches. Conjunctions of colour and orientation, as well as of colour and size, produced similar results.

It appears that not all conjunctive searches are equal, however. While the across-feature conjunctions cited above can be detected very efficiently, the same cannot be said of within-feature conjunctive searches. Such searches are defined by a combination of two features along one dimension, such as a search for a conjunction of colour and colour. Within-feature conjunctions typically produce search patterns suggestive of serial self-terminating searches (Wolfe, et al. 1990; Wolfe, et al. 1994; Bilsky and Wolfe 1995). Wolfe, et al. (1994) argue that this occurs because it is not possible for a single dimension to handle two requests simultaneously in the parallel-processing stage. Since the parallel stage can offer no guidance to the serial stage, the classic serial self-terminating search pattern results for such conjunctions.

More recent studies on within-feature conjunctions suggests that these types of search can be made more efficient by establishing a clear hierarchical relationship between features in a target. For example, research has shown that attention cannot be used to guide a search for a target house that is half red and half green; it can, however, be used to guide a search for a green target house that has red windows (Wolfe, et al. 1994). The authors of this study thus concluded:

> If search can be guided on the basis of the hierarchical relationship of patches of colour, it follows that the figural basis of that hierarchical relationship must be extracted in parallel prior to the serial deployment of attention.
> (Wolfe, et al. (1994,538)

The authors refer to such hierarchical relationships as relations between Parts and Wholes. This distinction between Parts and Wholes is at least partially defined by the concept of surroundedness, which is a term coined by psychologists. According to Wolfe, et al. (1994,544), "The more one region is surrounded by another, the more it seems to be a part." Their research on within-feature conjunctions established that searches for conjunctions employing a Part-Whole framework (e.g., green house with red windows) are more efficient than searches for the same type of conjunction using a Part-Part framework (e.g., house that is half red and half green). Similar results were obtained for within-feature conjunctions of size and size (Bilsky and Wolfe 1995).

CARTOGRAPHIC STUDIES OF THE VISUAL-SEARCH PROCESS

Cartographic research on visual-search processes is slowly expanding. Bartz (1970), who conducted one of the earlier studies in this area, evaluated the effect of typographic variations on subjects' abilities to detect names on a map. Maps of the set she designed for the experiment each had one, two, or three typeface variations. These variations included differences in typeface structure, style, and case. She then gave subjects a list of names to find on each map and recorded how long it took them to locate all the names. Results suggested that none of the typeface variations affected search times significantly. Bartz did note, however, that subjects' expectations played a role in search efficiency. If subjects had no expectations of the typeface in which a word would appear, and if mixed typefaces were used on the map, search times increased substantially.

Beller (1972) examined the effect that size and colour variations had on detecting numbers. He designed two circular graphs by arranging pairs of numbers, varying in either size or colour, along the perimeter of a circle. He then asked subjects to locate target numbers using these graphs, and recorded the time required to find each target. Two main findings stand out from this work. Beller found that numbers differing from the target number in either size or colour were easier to ignore than numbers differing from the target number only in numerical value. He also found that, as size differences between target and distractor numbers decreased, the time taken to detect the target number increased significantly.

More recently, Lloyd (1988) designed a map-reading task to assess which of three types of search process--parallel, serial self-terminating, or serial exhaustive--best described the visual-search process used in map reading. Subjects were divided into two groups, each performing a target-detection task--one group while examining a map, the other while accessing a map from memory. Reaction-time data showed that subjects who performed the task while viewing the map had search times indicative of a serial self-terminating search. Those subjects performing the task while accessing a memorized map, however, had search times indicative of parallel processing, suggesting that memory and perception tasks employ different visual-search strategies.

In 1993, Brennan and Lloyd completed a study that examined the visual-search process for locating boundaries on choropleth maps. They asked subjects to detect the presence or absence of a pre-cued target boundary, where the boundary was defined by two different colours used to fill adjacent polygons. Results suggested that search times increased with the addition of boundaries defined by two colours, where one colour was shared with the target boundary. This is indicative of a serial search process. Search times did not increase significantly, however, with the addition of boundaries that did not share colours with the target boundary--which is indicative of a parallel search process. These results led the authors to conclude that subjects were using a search process similar to Cave and Wolfe's (1990) Guided Search Model.

A study by Nelson (1994) evaluated the usefulness of Attentional Engagement Theory for modelling visual search for colour targets on bivariate choropleth maps. Subjects in this study were asked to detect the presence or absence of a pre-cued target colour on a test map. Nelson found that the most important factor affecting such searches was the similarity between the target and the distractors on the map. Since the similarity of distractors did not play a large role in search efficiency, Attentional Engagement Theory was not conclusively supported as a model for this particular search process. Furthermore, the author noted that it was difficult, if not impossible, to create maps that effectively represented Duncan and Humphrey's most difficult theoretical search condition (where the target is very similar to the distractors, but the distractors are very dissimilar to each other).

Lloyd (1997) continued his work on visual-search processes by focusing on colour's role in promoting search efficiency in a map environment. In this study, he constructed symbols that varied in colour, shape, size, and orientation. Subjects, shown isolated target symbols immediately followed by a map with symbols, were asked to indicate the presence or absence of the target symbol. His findings suggested colour was the most useful dimension for creating efficient single-feature searches. Combining colour with other unique dimensions also resulted in efficient parallel searches. Results of conjunctive searches using a combination of colour and some other feature indicated that such searches were generally serial self-terminating. He also noted that the location of the target on the map had a significant effect on reaction times.

METHODOLOGY

The focus of the present study was to examine the cognitive processes used by map readers when searching for multivariate point symbols on a map. The experiment used Chernoff Faces as the test symbol and a symbol-detection task to assess how accurately and how efficiently target symbols composed of different combinations of facial features could be detected. Of specific interest here was assessment of the role that different combinations of symbol dimensions and different combinations of symbol parts played in moderating search efficiency.

SUBJECTS

Ninety student volunteers from San Diego State University participated in the experiment. Students were solicited from several undergraduate geography classes. Those who participated received class credit for their time.

MAPS

The base maps used in the experiment were constructed from a digital file of county boundaries. The number of counties, and hence the number of distractor symbols on the map, varied randomly from trial to trial. The total number of counties on a map for any given trial was either nine, sixteen, or twenty-three. Chernoff Faces were constructed for each county using four fictitious datasets. For the purposes of explaining how the symbols would vary during testing, the datasets were presented to subjects as different types of crime data (Figure 1). Crime rates, total assaults, total larcenies, and total murders by county were the variables used in the explanation. Variations in head size, eye size, nose size, and mouth orientation were used to represent the different data values for each county. Each facial feature could accommodate one of two levels for a data value, either high or low.

EXPERIMENT

Each subject was tested individually using a 486 Pentium PC in a controlled testing environment. All subjects performed the same symbol-detection task. An isolated target symbol was first presented on the computer screen; this was immediately followed by a test map. The subject's task was to decide whether the target symbol was present, and to respond accordingly (yes or no) by pressing the appropriate key on the keyboard. The experiment consisted of five blocks of trials, with each block representing a search configuration common to multivariate symbols: (1) Feature searches, (2) Across-feature conjunctive searches for Part-Whole symbol combinations, (3) Across-feature conjunctive searches for Part-Part symbol combinations, (4) Within-feature conjunctive searches for Part-Whole symbol combinations, and (5) Within-feature conjunctive searches for Part-Part symbol combinations.

Feature searches are those in which the target symbol consists of a unique feature, allowing it to differ from the distractor symbols on a single dimension. In this study, for example, the key dimension might be head size, so that the head of the target symbol would have a unique size that differentiated it from all the distractor symbols (Figure 2a). Conjunctive searches, in general, are those in which half the distractors share one dimension with the target symbol and the other half share a second dimension with the target symbol. If the conjunction is an Across-feature Part-Whole conjunction, then the two dimensions will be different (e.g., size, orientation) and one dimension will be symbolized using the symbol Whole while the other will be symbolized using a symbol Part. Figure 2b provides an example by showing a target symbol that differs from half the distractors on head size (symbol whole) and the other half of the distractors on mouth orientation (symbol part). An Across-feature Part-Part conjunction is similar, but the two dimensions are now represented by two symbol parts. Here the target symbol might differ from half of the distractors on eye size and the other half of the distractors on mouth orientation (Figure 2c). In a Within-feature Part-Whole conjunction the two dimensions are the same; one is symbolized by the symbol whole and the other by a symbol part. Figure 2d provides an example showing a target symbol that differs from half the distractors on head size and the other half of the distractors on eye size. Finally, in a Within-feature Part-Part conjunction the two dimensions are the same and are represented by two symbol parts. Here the target symbol might differ from half the distractors on eye size and the other half of the distractors on nose size (Figure 2e).

Each block of trials in the experiment manipulated different combinations of facial features to create a set of trials for each type of search. For each block of trials, half the trials in the block had the target symbol present and half did not. For those trials in which the target symbol was present, placement of the symbol on the map was randomized. The presentations of all maps within a block were randomized, as were the presentations of the blocks themselves. Subjects completed a practice test beforehand to ensure that they understood the testing procedure and how to interpret the symbols.

HYPOTHESIS

Five hypotheses were tested using the experimental design described:

- Reaction times for feature searches should indicate that a parallel-search process was used to complete the task. This hypothesis has been substantiated throughout several visual-search studies (Treisman 1986; 1988; Wolfe, et al. 1989; 1990).
- Reaction times for conjunctive searches in general should be indicative of serial-search processes. Although researchers have established that some conjunctive searches can be completed using a parallel-search process, it is argued here that the complexity of the multivariate symbol/map environment will cause all such searches to be serial.
- Conjunctive searches across feature dimensions (e.g., size and orientation) should result in more efficient searches than conjunctive searches within feature dimensions (e.g., size and size). Wolfe, et al. (1990), Wolfe, et al. (1994), and Bilsky and Wolfe (1995) all produced data that suggest this to be a viable hypothesis for this study.
- Conjunctive searches within feature dimensions (e.g., size and size) should result in more efficient searches when a Part-Whole relationship is used to represent the dimensions than when a Part-Part relationship is used. This hypothesis is put forth on the basis of study results by Wolfe, et al. (1994) and Bilsky and Wolfe (1995).
- Error rates should be low for all searches examined, although increases in errors should be apparent for the more difficult conjunctive searches. Most visual-search studies have reported low error rates, with conjunctive searches exhibiting more errors than feature searches (Freidman-Hill and Wolfe 1995; Bilsky and Wolfe 1995).

RESULTS

The data collected were first edited to eliminate extreme reaction times. Using Tukey's outer-upper fences method (Tukey 1977), 693 out of a total 7,584 responses were tagged as extreme and eliminated from further analysis. To counteract skewness in the reaction-time data, a log transformation of data values was performed. The data were then aggregated over all subjects within each block of trials to compute mean reaction times and percent errors for target-present and target-absent trials with 9, 16, and 23 distractor symbols.

The reaction time data and percent error data for each of the five types of search were then further analyzed using analyses of covariance models (ANCOVA). The dependent variable in each model was either Reaction Time or Percent Error. The models used Response (Yes, No) as an independent variable, Number of Distractors as a continuous covariate, and Response*Number of Distractors as an interaction effect. An ANCOVA model is often used when it is not possible to control a covariate directly in an experiment. In this study, the independent variable Number of Distractors is a covariate because it is significantly correlated with the dependent variables. By using an ANCOVA, which is a combination of a regression analysis and an analysis of variance, the variation in the number of distractors associated with the dependent variable can be removed from the error variance. This results in more precise estimates and more powerful statistical tests (Stevens 1992).

FEATURE SEARCHES

Reaction Times

Contrary to the first hypothesis, figure 3a suggests that feature searches do not necessarily produce parallel search patterns in the context of multivariate map symbols. Analysis results indicated that mean reaction times increased significantly as the number of distractor symbols increased on each test map (Table 1). Search slopes (46.7 ms/item for Yes responses, 88.8 ms/item for No responses) were also significantly greater than zero for both No ($t(23) = 2.484$, $t = 0.021$) and Yes ($t(23) = 4.848$, $t = 0.003$) responses. Both results suggest that subjects used a serial search process in detecting the presence or absence of target symbols. Further evidence of a serial search can be found in the slope values themselves and in the ratio of slopes for No and Yes responses (1.9). Serial self-terminating searches typically have slopes greater than 20 ms/item, and the classic slope ratio of No to Yes responses is 2:1. As expected, No responses (2554 ms) always took longer to process than Yes responses (1905 ms), although this effect did not play a significant role in explaining the variance of responses in the model. The interaction effect was not significant either. This indicates that the rates of search for Yes and No responses do not differ significantly, although search slopes definitely suggest that target-absent searches are more difficult than target-present searches.

Percent Error
Error rates, as is common with this type of experimental task, were low for both Yes (.09) and No (.05) responses, and were not significantly affected by number of distractors, response, or the interaction of those two variables (Table 2). Conjunctive Searches

Reaction Times
Analyses for each of the four conjunctive searches also suggested that such searches were serial self-terminating (Figure 3b-e). Mean reaction times for Across-Feature Part-Whole searches, for example, increased significantly as the number of distractors increased on each test map (Table 1). The same held true for Across-Feature Part-Part searches, Within-Feature Part-Whole searches, and Within-Feature Part-Part searches. Slope values for each search type also furnished data supportive of serial search processes. Search slopes were significantly different from zero for both Yes and No responses for

- Across-Feature Part-Whole searches = 8.612, $t = 0.000$; $t(11) = 10.093$, $t = 0.000$),
- Across-Feature Part-Part searches = 6.056, $t = 0.000$; $t(23) = 9.998$, $t = 0.000$),
- Within-Feature Part-Whole searches = 9.295, $t = 0.000$; $t(23) = 12.338$, $t = 0.000$), and
- Within-Feature Part-Part searches = 4.987, $t = 0.000$; $t(11) = 6.989$, $t = 0.000$).

Search slopes for Yes and No responses were also significantly different from one another for Across-Feature Part-Whole searches, Across-Feature Part-Part searches, and Within-Feature Part-Whole searches (Table 1). Search slopes for the Within-Feature Part-Part search were not significantly different from one another, but the slopes for both Yes and No responses were over 100 ms/item, again indicating a serial search. Slope ratios also hovered around 2:1 for Across-Feature Part-Whole searches (1.8), Across-Feature Part-Part searches (2.1), Within-Feature Part-Whole searches (1.7) and Within-Feature Part-Part searches (1.5). In all cases, No responses took longer to process than Yes responses, but this effect did not play a significant role in explaining the variance of responses in any of the models.

Percent Error
As Figure 3b-e shows, error rates--although still low--were generally higher for these searches in comparison to Feature searches, especially for Yes responses. This trend is most apparent for the Part-Part conjunctive searches, a finding that was also noted by Bilsky and Wolfe (1995). Errors also tended to increase with the number of distractors for Yes responses, although this was not a significant effect in any of the models except the Within-Feature Part-Part search (Table 2). No other significant trends were noted. Response, except for the Across-Feature Part Whole model, did not play a significant role in explaining the variance in percent error for the models examined. The same can be said of the interaction of Response*Number of Distractors.

COMPARING SEARCH TYPES

To assess the validity of the remaining hypotheses, target-present searches for each search type were compared. Using analyses of covariance models, reaction-time data and percent-error data were used to analyze the differences in the five search types examined in this study. The dependent variable in each case was either Reaction Time or Percent Error. The models used Search Type as an independent variable, Number of Distractors as a continuous covariate, and Search Type*Number of Distractors as an interaction effect.

Reaction Times

Figure 3f clearly shows a hierarchy of search efficiency for the five search types. Feature searches appeared to be the most efficient and searches for Part-Part relationships the most difficult, regardless of whether the search was for an Across-Feature or Within-Feature conjunction. Results from the statistical analysis confirmed that the search slopes for the five search types were significantly different, which supports the visual interpretation of this data (Table 3). It does not appear, however, that searches for Across-Feature conjunctions are always more efficient than those for Within-Feature conjunctions, as was hypothesized. Rather, the data from this study suggest that in the context of multivariate symbols the use of hierarchical relationships plays the more important role in determining search efficiency. As expected, searches for Within-Feature conjunctions were more efficient when Part-Whole relationships were used as opposed to Part-Part relationships.

Percent Error

Error rates were fairly low for most searches, with a significant increase occurring as the number of distractors on the test maps increased. Figure 3f also suggests that error is higher across the board for searches employing a Part-Part relationship, although neither Search Type nor the interaction of Search Type*Number of Distractors played a significant role in explaining variance in percent error.

DISCUSSION

Results from this study provide valuable insights into the nature of searching for multivariate point symbols in a map environment. Data from the experiment do not support, for example, the hypothesis that all feature searches are completed using parallel search processes. Rather, this study indicates that some feature searches result in serial search processes being used to detect target symbols. While the majority of visual-search studies conducted are supportive of the link between parallel processing and searching for symbols with unique features, the results of this study are not uncommon. Others who have obtained similar results include Treisman and Gormican (1988) and Lloyd (1997). Indeed, such results should not be unexpected in this study. The complexity of Chernoff Faces, along with the placement of such symbols on a map, most likely increased noise levels considerably during the search process, effectively lengthening search times.

The choice of facial features on which to map the data, as well as the choice of graphic dimensions to manipulate for each feature, probably also likely played roles in this finding. For example, some researchers have noted that facial features seem to vary in levels of perceptual importance (Huff and Black 1978). Such findings suggest that the choice of features used in the face may influence how quickly and/or accurately subjects are able to detect any given symbol. A pilot study conducted prior to this research did not indicate any significant differences in subjects' abilities to discriminate pairs of Chernoff faces on the basis of any one facial feature used in this study. However, the data collected from feature searches in this experiment suggest a different story. Results of an analysis on feature searches indicate that subjects were the fastest and most accurate when detecting changes in head size. They had the most trouble detecting changes in mouth orientation; eye size and nose size fell somewhere in between. Even so, all searches were still serial, suggesting that differences in the facial features chosen for this study is not the primary cause of increased search times.

Perhaps more important than the facial feature used is the graphic dimension varied for each facial feature. This study examined only two graphic dimensions, size and orientation. Several other studies, however, including Lloyd (1997) have found that for the most efficient feature searches one should use colour as the discriminating graphic dimension. The use of colour in this study would quite likely have had the same impact. In fact, colour is such a highly effective graphic dimension that one might even argue against using it in a multivariate symbol.

Mapping only one of several variables to a multivariate symbol using colour might provide to the variable mapped an unwanted perceptual edge over the other datasets symbolized. Of course, if the goal is to emphasize one of many variables, colour might be the best alternative. Clearly, colour is one of cartography's most powerful graphic dimensions and should be used with care.

Although not suggestive of parallel searches, the feature searches in this experiment were by far the easiest for subjects to complete, as is evidenced by the much shallower slopes associated with them. Conjunctive searches, on the other hand, had much steeper search slopes. This type of search does not have a target symbol with a unique feature separating it from the other symbols on the map. The lack of a unique identifier for the target makes the search less efficient. Analyses on searches of this type suggest that they, like feature searches, were completed using a serial self-terminating search process. Such findings are supported heavily in the literature, in both cartography and psychology (Treisman 1986; 1988; Cave and Wolfe 1990; Wolfe, et al. 1994; Bilsky and Wolfe 1995; Lloyd 1997).

The most intriguing results of this study are connected to the differences found among the types of conjunctive search examined. These findings have special implications for the design of multivariate point symbols. For instance, analyses suggest that symbol combinations exploiting Part-Whole relationships were more easily processed than those exploiting Part-Part relationships, regardless of whether the search was for an Across-Feature conjunction (e.g., size and orientation) or a Within-Feature conjunction (e.g. size and size). How can cartographers effectively use such information? Take a case in which a map is being designed using multivariate point symbols, and the cartographer wishes to highlight certain data combinations within the symbols. This research suggests that he could do so from the perspective of search efficiency by assigning one variable to the symbol whole and another to a symbol part. There is support for such results not only in the visual-search literature (Wolfe, et al. 1994, Bilsky and Wolfe 1995), but also in the literature on physiology. The work of Robertson and Lamb (1991), for example, suggests that global properties are processed in the right hemisphere of the brain, while local properties are processed in the left hemisphere. Assuming this is accurate, processing a search for a symbol using a Part-Whole relationship would potentially make use of both hemispheres of the brain. A search for a symbol that uses a Part-Part relationship to symbolize the data, however, would have to rely on only the left hemisphere for processing, which theoretically could decrease search efficiency.

Data from this study, in contrast to results from previous visual-search studies, do not support the notion that Across-Feature conjunctive searches are processed significantly more easily than Within-Feature conjunctive searches. This study, however, is the only one of which the authors are aware in which hierarchical relationships were examined in relation to searches for both Within-Feature and Across-Feature conjunctions. This more detailed examination of search types may play a role in this discrepancy. In this study, for example, Across-Feature conjunctions exploiting Part-Whole relationships are indeed easier to process than Within-Feature conjunctions exploiting either relational combination. Across-Feature conjunctions of Part-Part relationships, however, were the most difficult searches to perform according to study results. Why?

To make sense of this finding, one must return to the multivariate symbol itself and examine the symbol dimensions used to code the data values. Lloyd found that, of the four dimensions he tested (size, shape, colour, and orientation), orientation proved to be the least effective in single-feature searches. A subsequent analysis of the feature searches performed in this study produced comparable results. In addition, both Wolfe, et al. (1994) and Wolfe and Bilsky (1995) found that they could not replicate the differences in search efficiencies for Within-Feature Part-Whole and Part-Part searches when the symbol dimensions manipulated were orientation and orientation. Searches were serial in both instances here.

Speculation about this finding revolves around the concept of feature invariability (Wolfe et al. 1994; Bilsky and Wolfe 1995). These authors have proposed that a feature such as orientation is easily altered; since perception of such features can change with the rotation of an object, searching for it theoretically becomes more difficult. Such features as colour and size, on the other hand, are invariant. Since all Across-Feature Part-

Part conjunctions used orientation as one dimension in defining the target symbols, perhaps the use of this symbol dimension counteracted any positive effect that Across-Feature searches would hold over Within-Feature searches. If so, it would seem plausible to argue that hierarchical relationships alone were what kept Across-Feature Part-Whole searches more efficient than either Within-Feature conjunctive search. This is not to say, however, that Across-Feature conjunctions would not be more efficient in situations where there are no hierarchical relationships to exploit.

CONCLUSIONS

This study has taken the theories of visual-search processes and applied some of their concepts to searching for multivariate point symbols in a map environment. Many of the results are similar to those found in previous cartographic and psychological studies; other results suggest that the map environment complicates the process. As all cartographers are aware, maps in the real world are generally much more complex than those used in an experimental context. This study is no different in that regard; the maps and symbolization were intentionally kept simple to control any extraneous information or variables that would unduly influence the search process being studied. Likewise, the experimental task was a rather restricted one. Subjects had only to indicate whether or not the symbol was present on the map. No data interpretation was required of them for the purposes of this particular experiment.

Cartographic design is a rich and varied endeavour, where there are always multiple solutions to any one problem of symbolization. Cartographers have their choice of several symbol designs and many graphic variables. This study restricted itself to examining search processes for one type of symbol--the Chernoff Face--and two graphic variables--size and orientation. The results offer cartographers many useful insights into the design of such symbols. Research results demonstrated that hierarchical relationships could be manipulated within these types of symbol to increase search efficiency, for example. Results also suggested that all symbol dimensions are not created equally from the perspective of visual search, and that this has an impact on search efficiency when trying to implement techniques for improving search on maps. Research needs to be extended in future studies to examine other symbol designs and to evaluate all the graphic variables commonly used in cartographic production. It will also be important to study the implementation of these results in a more strenuous task environment where subjects are required to interpret the data represented by the symbols on the map. Other interesting avenues of research include further evaluating the Part/Whole concept as it applies to other cartographic symbols, and studying Chernoff Faces more critically. For example, is the whole of a Chernoff Face really the size of the circle--as implied in the psychological literature--or would the coordination of features to create a happy, sad, or angry face be a more useful whole from a cartographic standpoint? Visual-search theories provide cartography with useful models for attempting to understand and model search in a map environment, and they should be studied and applied whenever one of the cartographer's goals is to provide efficient searching of a map.

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((1)) (Board and Wilson 1966; Carstensen 1982; 1984; 1986; Lavin and Archer 1984; Olson 1981; Wainer and Francolini 1980; Eyton 1984). Chang (1982,103).

Table 1 ANCOVA Summaries for Reaction Times.
Legend for Chart: A - Type of Search B - Response (Y,N) Mean RT(ms) DF

C - Response (Y,N) Mean RT(ms) F
D - Response (Y,N) Mean RT(ms) P >F
E - Number of Distractor Symbols DF
F - Number of Distractor Symbols F
G - Number of Distractor Symbols P > F
H - Response*Number of Distractors (Y,N) Slopes DF
I - Response*Number of Distractors (Y,N) Slopes F
J - Response*Number of Distractors (Y,N) Slopes P >F

A	B	C	D
	E	F	G
	H	I	J
Feature (R^2 = 0.45)	(1,47)	0.002	(1905, 2554) 0.963
	(1,47)	19.963	0.000
	(1,47)	1.925	(46.7, 88.8) 0.172
Across Part-Whole (R^2 = 0.93)	(1,23)	0.451	(2334, 3210) 0.510
	(1,23)	172.620	0.000
	(1,23)	15.165	(79.5, 146.5) 0.001
Across Part-Part (R^2 = 0.87)	(1,47)	0.016	(3791, 5930) 0.901
	(1,47)	134.466	0.000
	(1,47)	16.520	(119.9, 249.4) 0.000
Within Part-Whole (R^2 = 0.91)	(1,47)	284	(2587, 3667) 0.597
	(1,47)	238.604	0.000
	(1,47)	17.369	(80.4, 139.8) 0.000
Within Part-Part (R^2 = 0.89)	(1,23)	2.491	(3003, 5021) 0.130
	(1,23)	72.142	0.000
	(1,23)	2.488	(134.1,195.2) 0.130

Table 2 ANCOVA Summaries for Percent Error.

Legend for Chart:

A - Type of Search
B - Response (Y,N) Mean RT(ms) DF
C - Response (Y,N) Mean RT(ms) F
D - Response (Y,N) Mean RT(ms) P >F
E - Number of Distractor Symbols DF
F - Number of Distractor Symbols F
G - Number of Distractor Symbols P > F

H - Response*Number of Distractors (Y,N) Slopes DF I - Response*Number of Distractors (Y,N) Slopes F J - Response*Number of Distractors (Y,N) Slopes P >F			
A	B	C	D
	E	F	G
	H	I	J
Feature (R^2 = 0.09)	(1,47)	0.441	(0.09, 0.05) 0.508
	(1,47)	0.734	0.394
	(1,47)	2.519	(-0.004, 0.011) 0.116
Across Part-Whole (R^2 = 0.17)	(1,23)	7.341	(0.09, 0.10) 0.010
	(1,23)	0.266	0.608
	(1,23)	7.767	(-0.006, 0.004) 0.008
Across Part-Part (R^2 = 0.37)	(1,47)	0.672	(0.17, 0.04) 0.414
	(1,47)	2.889	0.093
	(1,47)	2.443	(-0.006, -0.000) 0.122
Within Part-Whole (R^2 = 0.08)	(1,47)	0.478	(0.09, 0.06) 0.491
	(1,47)	1.760	0.193
	(1,47)	2.177	(-0.003, 0.000) 0.143
Within Part-Part (R2 = 0.34)	(1,23)	0.150	(0.17, 0.03) 0.700
	(1,23)	4.601	0.038
	(1,23)	3.340	(-0.013, 0.001) 0.083

Table 3 ANCOVA Summaries comparing search types for target present searches: Reaction Time and Percent Error.			
Legend for Chart: A - ANCOVA Model Dependent Variable B - Search Type DF C - Search Type F D - Search Type P > F E - Number of Distractor Symbols DF F - Number of Distractor Symbols F G - Number of Distractor Symbols P > F H - Search Type*Number of Distractors DF I - Search Type*Number of Distractors F J - Search Type*Number of Distractors P > F			
A	B	C	D

	E	F	G
	H	I	J
Mean Reaction Time ($R^2 = 0.84$)	(4,95)	1.881	0.121
	(1,95)	139.680	0.000
	(4,95)	4.472	0.002
Mean Error (Percent) ($R^2 = 0.18$)	(4,192)	0.551	0.699
	(1,192)	17.780	0.000
	(4,192)	1.028	0.394

DIAGRAM: Figure 1 Graphic used to explain concept of Chernoff Faces to subjects.
FIGURE 1 IS OMITTED FROM THIS FORMATTED DOCUMENT

DIAGRAM: Figure 2 Examples of different searches: (a) Feature, (b) Across-Feature Part-Whole, (c) Across-Feature Part-Part, (d) Within-Feature Part-Whole, and (e) Within-Feature Part-Part.
FIGURE 2 IS OMITTED FROM THIS FORMATTED DOCUMENT

GRAPH: Figure 3 Mean reaction times (lines) and percent error (bars) for the five search types: (a) Feature Search, (b) Across-Feature Part-Whole Search, (c) Across-Feature Part-Part Search, (d) Within-Feature Part-Whole Search, (e) Within-Feature Part-Part Search, and (f) the five target-present search types together.
FIGURE 3 IS OMITTED FROM THIS FORMATTED DOCUMENT

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