Colour Detection on Bivariate Choropleth Maps: The Visual Search Process

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Abstract:
Searching is a fundamental but complex task in the map-reading process. Several psychologists have explored the role of visual search in cognition, and have proposed a number of models that may offer cartographers a basis for understanding how people search for specific map information. The purpose of this research was to examine the visual search process used by map readers when interacting with bivariate choropleth maps, and to assess the potential of one of psychology's models, Attentional Engagement Theory, for explaining that process. The study employed a standard search task that determined the efficiency of the search process by having subjects search for target colours among non-target colours across a map. An analysis of reaction times showed that the following variables affected search efficiency: target colour, the total number of objects on the map, and similarity of the target colour to all other non-target colours on the map.
Keywords: visual search, cartography–colour, bivariate map.

Article:
Introduction
The mechanics of the map-reading process are complex, and have yet to be precisely defined by cartographers. Shortridge (1982: 155) described map reading in general terms as a "... multi-step process ranging along the perceptual-cognitive continuum." She also identified several steps of this process, believed to be fundamental to map reading: symbol detection through search, symbol classification by comparison, and information synthesis. This study focuses on the first of these steps, symbol detection through search.

Locating the name of a city and detecting the lightest or darkest shaded region on a map are two examples of the type of search processes that map readers may undertake in a cartographic environment. Such searches represent a dynamic interaction between the map and the map reader (Dobson, 1985), and an understanding of this interaction is essential if cartographers hope to comprehend the map-reading process. Visual search research will contribute to cartographic knowledge by providing insight into the interaction between map and map reader; knowledge of this interaction will allow cartographers to improve the communicative aspects of maps, as well as provide valuable information to those designing GISs and other expert systems for cartographic applications.

Cartography and the Visual Search Process
Research concerning the visual search process is still relatively scarce in cartography. 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. By manipulating the use of all-capital lettering versus upper-and-lower case lettering, light typefaces versus bold typefaces, and the use of mixed typefaces versus one standard typeface, Bartz designed a set of maps so that each map had from one to three typeface variations. She then gave subjects a list of names to find on each map, and recorded how long it took them to find all names. Results showed that none of the typeface variations affected search times significantly; however; when mixed typefaces were used and subjects had no expectations of the typeface in which a word would appear, search times increased substantially.

Beller (1972) examined the effect that size and colour variations had on detecting numbers. He first designed two circular graphs by arranging pairs of numbers, varying either in size or in 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. Results of his study suggested the following:

1) 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, and

2) As size differences between target and non-target numbers decreased, the time it took to detect the target number increased significantly.

More recently, Lloyd (1988) designed a map-reading task to assess which of three types of search processes—parallel, serial self-terminating, or serial exhaustive—best described the visual search process used in map reading. Subjects, divided into two groups, performed a target detection task either while looking at a map or 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, which suggests 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 filling adjacent polygons with two different colours. Results showed that search times increased with the addition of boundaries that shared one colour with the target boundary (indicative of a serial search process), but search times did not increase significantly with the addition of boundaries that did not share colours with the target boundary (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.

The purpose of this study is to examine the visual search process used by map readers when interacting with bivariate choropleth maps. The particular map-reading task used to evaluate this process was the detection of map symbols, identified by Shortridge (1982) as one of the primary tasks performed in the map-reading process. An assessment of the techniques used in symbol detection should provide cartographers with valuable information about this step of the map-reading process. In addition, results of this study should provide insight into the efficacy of bivariate choropleth maps for representing spatial and statistical data.

MODELS OF VISUAL SEARCH

Research by psychologists offers cartographers a basis from which they can begin to study how humans search maps for information. 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 non-target items. Targets can be defined in a number of ways:

1) by a single feature, such as size or colour;

2) by a conjunction of features, such as the combination of colour and shape, or

3) by a variety of other complex properties, such as a search for the digit 2 among 5s (Wolfe, 1994). The number of non-targets varies across trials, and the experimenter records subjects' reaction times for each trial.

Variation in reaction time as a function of the number of non-targets present (known as set size) is then used to make inferences about the underlying structure of the visual search process (Wolfe, 1994). For instance, when reaction times are dependent on set size, the search is a serial process; subjects must focus on each item in a visual field to assess target presence or absence. When reaction times are independent of set size, though, the search is a parallel process, because subjects determine target presence or absence without focusing on individual items in the visual field. Examining the search processes in this way has led psychologists to propose a number of models that outline the stages of the visual search process.

FEATURE INTEGRATION THEORY

One of the central ideas in early visual search models was that visual processing occurred 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 claims that the human visual system first perceives the elementary attributes of a scene, such as colour and shape. Perception of these attributes occurs in parallel across the visual field, yielding a number of *feature maps,* each of which represents one of these elementary attributes. 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 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 first conjoin the feature maps of redness and squareness to detect the target item.

One of the first studies that supported this theory required subjects to search for a green T among a field of green Xs and brown Ts (Treisman and Gelade, 1980). Because the T shared one attribute with each of the non-target items, subjects had to form a conjunction of those attributes to detect target presence. Results of the experiment showed that reaction times increased linearly with an increase in set size, suggesting that subjects were attending to each object to verify these feature conjunctions. A similar task, designed to examine the rudiments of feature searches, showed that subjects could reject non-targets in parallel when the target item had a unique feature (for example, a search for a blue letter among green Xs and brown Ts). Reaction times in this case did not increase linearly with an increase in set size. The element of shape produced a similar pattern of results. The authors also found that feature discriminability played a role in the efficiency of the search task. When comparing a search for a green T among green Xs and blue Ts to a search for a red 0 among green Os and red Ns, they found that searches took longer when target colours were more similar to non-target colours.

Both Treisman and Gormican (1988) and Treisman and Souther (1985) examined the role of search asymmetry in visual search tasks. Search asymmetry is defined as that which occurs when reaction times differ significantly for a task depending on which object serves as the target and which as the non-target. For example, Treisman and Souther (1985) found that when the target was an O and the non-targets were Os with intersecting lines, searches were serial, even though the search was actually a feature search. However, when the target was an O with an intersecting line and the non-targets were Os, reaction times behaved as expected, indicating that activity from a unique feature must signal the presence of a *target* to generate a parallel search. Treisman and Gormican (1988) obtained the same results in a similar study.

More recently, researchers studying visual search have found that conjunctive searches involving simple features are not necessarily serial in nature, as Treisman's model assumes, but may result in reaction times that indicate a parallel search process (Reisman and Sato, 1990; Wolfe, et al., 1989; Wolfe, et al., 1990). For example, Feature Integration Theory predicts that a search for a red N in a field of green Ns and red Os will be serial because the target is composed of a conjunction of features. Other researchers have suggested, however; that the parallel stage of the search process guides the subsequent serial process, allowing such conjunctive searches to result in parallel search times (Wolf, et al., 1989; Wolf, et al., 1990). Since the parallel process can differentiate between the red and green of the previous search example, it appears logical to use that process to guide the subsequent serial process in eliminating all green items from the search array. Such theorizing led

Cave and Wolfe (1990) to propose an alternative theory to Feature Integration Theory, the *Guided Search Model.*

GUIDED SEARCH MODEL

Cave and Wolfe's (1990) model is a modification of Feature Integration Theory, in which the interactions between the parallel and serial processing stages are different. The Guided Search Model describes the visual search process in the following manner: First, for each feature dimension (i.e., colour, shape, size) that is part of the visual field, the parallel processing stage identifies the location that has a value closest to the target value for that feature. Feature values for each location are then summed, yielding an *activation map* in which the values for each location describe the likelihood of the target existing there. The serial stage of processing chooses the location in the activation map with the highest activation value as a potential match for the target (Cave and Wolfe, 1990). Consider, as an example, a target consisting of a red square and non-targets consisting of green squares and red triangles. Under the Guided Search Model, the parallel processing stage is sensitive to the features of colour and shape. While neither feature on its own can identify a target, each feature dimension guides attention to the critical values within that dimension—in this case, the values of redness and squareness. The information provided by these values allows the parallel *stage* to guide the serial stage to the target item (Wolfe, et al., 1990).

The parallel stage of the search process is composed of three components: bottom-up information, top-down information, and noise (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 non-targets leads to very strong bottom-up activation because the non-targets 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. Because it is the parallel stage that combines information from all feature dimensions by using bottom-up and top-down processing, it should theoretically be possible to find conjunctive targets as easily as feature targets. However; a noise component in the system prevents this from happening. The manipulation of noise within the system causes search times to vary, from those in which set size is not a factor in explaining reaction times, to those in which set size significantly affects reaction times. Thus, the parallel stage can never determine the target, but can only suggest probable choices to the serial stage, which then processes each possibility until an answer is found. If the level of noise is low, then the serial 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, then 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 behavior 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 showed 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. Even more telling was an experiment designed to test search times for triple conjunctions. Feature Integration Theory predicts that triple conjunctions will be more difficult to process than standard conjunctions, due to their complexity. The Guided Search Model, however; approaches the search for triple conjunctions differently. This model predicts that multiple sources of information will provide a more efficient search by giving better guidance to the serial stage. Results of this experiment also supported the Guided Search Model.

ATTENTIONAL ENGAGEMENT THEORY

Another important visual search model that shares many properties with the Guided Search Model is *Attentional Engagement Theory* (Duncan and Humphreys, 1989, 1992). This model addresses the effects of similarity on search efficiency. Two types of similarity attributes form the basis of this theory:

1) T-N similarity is a measure of how similar a target is to all competing non-targets, and

2) N-N similarity is a measure of how similar all non-targets are to one another.

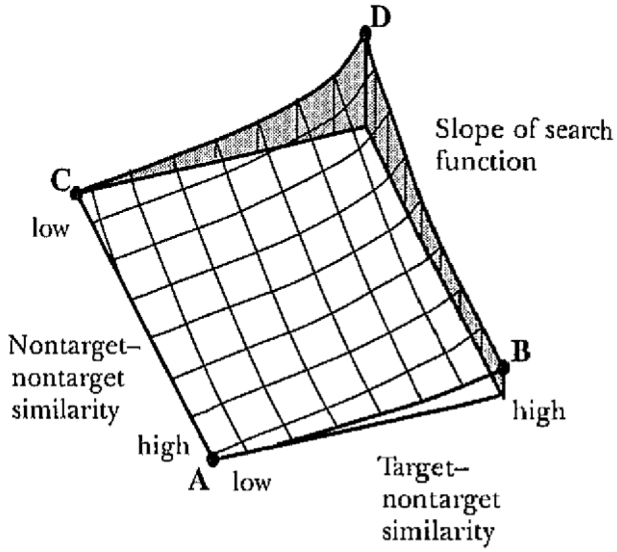


Figure 1. Search Surface. After Duncan and Humphreys, 1989.

A plot of the authors' theoretical search surface explains how these two variables interact to affect the visual search process (Figure 1). Duncan and Humphreys (1992) associate five premises with this surface:

1) The configuration of the surface suggests that search times will vary continuously across search tasks and conditions, rather than support the idea that searches are either serial or parallel, based on task type.

2) When *T-N* similarity is low (line AC), search times will be efficient, regardless of N-N similarity.

3) Likewise, when *N-N* similarity is high (line AB), search times will also be fairly efficient, showing only small increases in time as T-N similarity increases.

4) When *N-N* similarity is low (line CD), T-N similarity becomes a much more important indicator of search efficiency.

5) Likewise, when T-N similarity is high (line BD), N-N similarity is an important indicator of search efficiency.

Generation of this search surface begins with "... a parallel stage of perceptual segmentation and analysis ...," where specific information is chosen from the visual field and recorded into visual short-term memory (VSTM) (Duncan and Humphreys, 1992: 578). Selection of information is competitive. The search process assigns weights to each location in the visual field, and the strength of the weight determines how successful the location will be in gaining access to VSTM.

Two types of similarity influence the weight assignments (Duncan and Humphreys, 1989). *Interalternative similarity* categorizes each location in the visual field either as a potential target or as a non-target. Once categorized, the selection process continues by determining how well the location description matches an attentional template of the target. Thus, location weights will increase or decrease in proportion to how well the location matches the template. *Within-display similarity* measures the similarity of locations to one another. All locations are linked, and a change in weight for one location affects all other locations according to the strength of the perceptual grouping. Such weight redistribution means that the search process can efficiently reject strongly grouped non-targets by means of *spreading suppression* (Duncan and Humphreys, 1989; 1992). According to this theory, then, two types of similarity attributes strongly influence search behavior:

1) interalternative similarity, which categorizes each location as either target or non-target, and where increases in T-N similarity are detrimental; and

2) within-display similarity, which compares the similarity of one location to another, and where decreases in N-N similarity are detrimental.

Both Duncan (1989) and Farmer and Taylor (1980) conducted experiments that supported this theory. Duncan (1989) tested the merit of Attentional Engagement Theory by using simple colour patches as stimuli in a target-detection task. He created six colours designed to be maximally dissimilar to one another. Holding dissimilarity between non-targets constant, he then used each colour as a target value among a field of non-target colour patches. Resulting search times indicated that the effects of increasing set size depended on the similarity of the patches added to the target colour.

In a second experiment, Duncan (1989) obtained similar results with a target detection task that manipulated N-N similarity as well as T-N similarity. In this instance, he first created two sets of colours. *Widely-spaced* colours ranged from red to green, and *narrowly-spaced* colours ranged from red to purple. The narrowly-spaced set, consisting of a smaller range of colours, was higher in N-N similarity than the widely-spaced set. Duncan then divided each colour set into smaller sets of target colours and non-target colours. For example, in the widely-spaced set, the colours included were red, orange, yellow, and green. When partitioning the set, Duncan created two conditions by using the placement of colours on a standard colour wheel as a guide. In the first condition, he defined T-N similarity as high because target colours were located between the non-target colours (targets were yellow and orange; non-targets were red and green). In the second condition, he defined T—N similarity as low because target colours were not located between non-target colours (targets were red and green; non-targets were yellow and orange). When subjects performed target detection tasks for each set of colours and for both conditions, reaction times supported Attentional Engagement Theory by showing that search difficulty increased under the following conditions:

1) when widely-spaced colours were used (N-N similarity / decreased), and

2) when defined target colours were located between non-target colours (T-N similarity increased).

Farmer and Taylor (1980) completed their study before the formation of Attentional Engagement Theory, but their results support the basic premises of this model. They examined the influence of both background uniformity (N-N similarity) and T—N similarity on target detection. Stimuli for their target detection tasks were gray patches that varied in brightness, and colour patches that varied in hue. Subjects participating in the experiment searched for a gray target among a field of coloured non-targets, or background items. Results of this work suggested that similarity in brightness between gray targets and coloured non-targets (T-N similarity) as well as similarity in hue for the coloured non-targets (N-N similarity) significantly influenced search times.

The Experiment

This study assessed the visual search process used by map readers while they are interacting with bivariate choropleth maps. The experiment consisted of a symbol-detection task designed to test how well Attentional Engagement Theory (Duncan and Humphreys, 1989, 1992) explained the search process used by map readers in completing this task.

Subjects

All subjects were volunteers, and students at the University of South Carolina. Ten subjects participated in the pilot test, and twenty-six participated in the main experiment.

Pilot Test

The first step in assessing the visual search process used on a bivariate choropleth map was to create a palette of colours suitable for mapping data in this manner. In addition, since Attentional Engagement Theory requires that each map tested be categorized by the interaction of two similarity indices (T-N and N-N), it was necessary to measure the perceptual similarities of the colours. Nine colours, similar to those used by the Bureau of the Census for their 1970s bivariate choropleth map series (Meyer et al., 1975), were generated using the RGB colour system on an IBM PC (Figure 2). A paired comparison experiment was then conducted to assess the perceptual similarities of the nine colours. Subjects, tested individually in a computer environment (thirty-six trials), judged the similarity of all possible colour combinations on a scale of 0-100. They used a mouse to click on the appropriate place along a computer-generated scale to record the numerical value of similarity for each colour pair. These similarity ratings were then analyzed using multi-dimensional scaling, which created a perceptual colour space where the nine colours were mathematically spaced according to subjects' perceptions of their similarity. This colour space was subsequently used to calculate the similarity measures required to quantitatively define Duncan and Humphreys' theoretical search surface (Figure 1).

Percent High School Completed	Median Family Income: Less than 10,000	10,000–30,000	Above 30,000
70.0+	Green R G B 20 35 0	Blue-green R G B 20 30 25	Dark Violet R G B 15 15 20
50–69.9	Light Green R G B 30 50 0	Light Brown R G B 40 40 20	Red-brown R G B 30 25 20
0–49.9	Yellow R G B 63 55 0	Orange R G B 60 35 0	Red R G B 50 10 0

Figure 2. Legend Colours (Defined using an RGB model, 0–63 value range).

MAIN EXPERIMENT

After defining the colour space to be used in calculating the similarity indices, base maps with nine, seventeen, twenty-five, and thirty-three counties were created from a computer file of digitized county boundaries (Figure 3). All possible colour combinations for a nine-county map were then generated by computer. Thus, map complexity could range from a simple two-colour map (one target colour and one non-target colour used in eight polygons) to a diverse nine-colour map (one target colour and eight non-target colours). T—N and N—N similarity indices were defined for each of these maps by using the perceptual colour space generated in the pilot test. To calculate T—N similarity for a map, the Euclidean distances in the space between each non-target colour and target colour on the map were calculated. These distances were then added together and divided by the total number of colours used on the map. N—N similarity was calculated by determining the Euclidean distances between all non-target colours on the map, then summing those distances and dividing by the total number of colours used on the map.

The minimum and maximum values of both similarity measures over all possible nine-county maps quantitatively defined Duncan and Humphreys' hypothesized search surface. To ensure that the maps generated covered the entire search surface, the surface was divided into nine sectors, and the first ten nine-county maps that met the similarity index requirements for each sector were chosen to represent that part of the search surface (Figure 4). Since the standard target detection task requires trials to vary the number of non-targets present on the map, maps with seventeen, twenty-five, and thirty-three counties were also created. These maps were derived flora the nine-county maps in the following manner: Each nine-county map was expanded into a seventeen-county, twenty-five-county, and thirty-three-county map by adding additional county boundaries from the digital file and then filling each new county with one of the non-target colours already in use on the nine-county map. For example, a seventeen-county map used the same target values as the nine-county map, but had each oldie nine-county non-target values represented twice. All maps consisted of either nine, seventeen, twenty-five, or thirty-three counties, and were composed of some combination of the nine legend colours. Subjects viewed a total of 320 maps, with forty maps falling into each sector.

Figure 3. Seventeen-county map example.

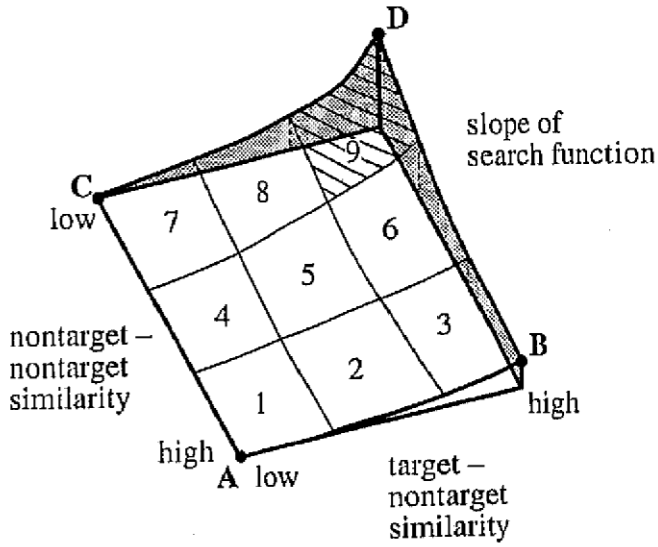


Figure 4. Search surface divided into sectors.

It is important to note, at this point, that none of the map combinations generated by computer fell within the boundaries of Sector 9 (Figure 4). Sector 9 is the area of the search surface where T—N similarity is *highest* and N-N similarity is *lowest.* By this definition, the absence of maps in this sector makes sense; no bivariate choropleth map created for this experiment existed where the target colour was maximally similar to all non-target admire while at the same time all non-target colours were maximally *dissimilar* to one another. Since Duncan and Humphreys (1989) did not quantitatively define their search surface, this would seem to indicate that, at least for this study, their search surface is in need of modification. For the purposes of this research, then, Sector 9 was not used, and does not show up as part of the revised, quantitatively defined search surface used in this study.

Subjects, tested individually, sat at a computer and searched for pre-cued target colours on a series of test maps that were displayed on the computer screen. The computer indicated the target colour for each trial by displaying the map legend on-screen and highlighting the target colour. It then replaced the legend with a blank screen, followed by a map. The subject responded to the presence or absence of the target colour by pressing one of two keys on the keyboard. Of the 320 trials presented, half had the pre-cued target on the map and half did not. Reaction times were recorded for each trial. The presentation of all maps was randomized.

Hypotheses

This study examined four hypotheses, each of which stemmed from the principles that formed Attentional Engagement Theory.

1) Search efficiency should vary continuously across search tasks and conditions.

2) Search efficiency should decrease with increasing similarity between targets and non-targets.

3) Search efficiency should decrease with decreasing similarity between non-targets and non-targets.

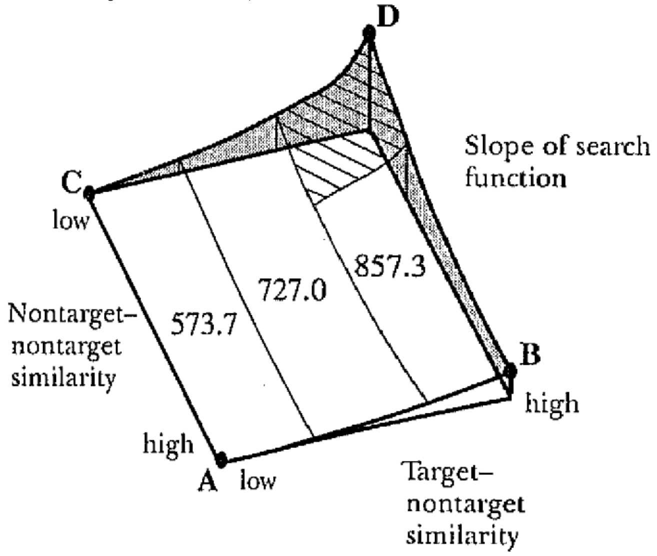
4) T—N similarity and N—N similarity should interact to scale each other's effects.

ANALYSES AND RESULTS

The raw data file was edited to eliminate extreme reaction times as identified by Tukey's outer-upper fences (Tukey, 1977). This procedure eliminated seventy of 4,160 responses, approximately 2% of the data. Because subject responses were skewed, as usually happens in reaction time experiments, the geometric means for the remaining correct responses were computed by averaging all subject responses across all categories. Trials with incorrect responses were treated as missing data in the analyses, also a standard procedure for reaction time experiments. Results of the study are summarized in the following paragraphs, figures, and tables.

Analysis of Variance

The dependent variable in this analysis was reaction time. Independent variables were T—N similarity, N—N similarity, set size (the number of counties on the map), and target colour.



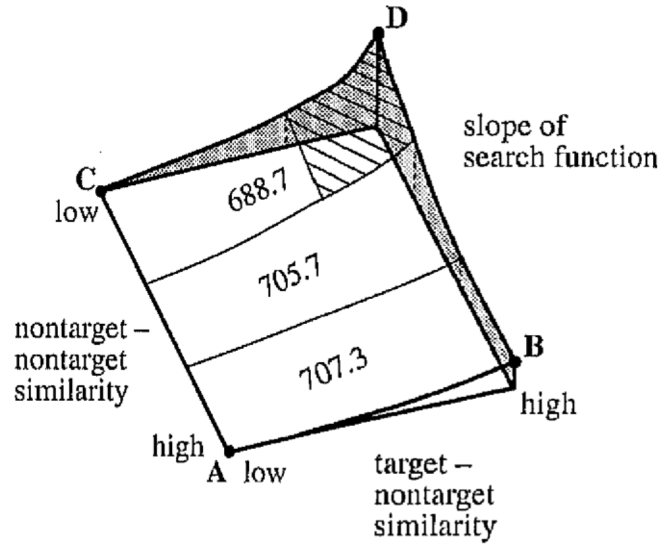


Figure 5. Mean reaction times (msecs) for T–N similarity levels.

Figure 6. Mean reaction times (msecs) for N–N similarity levels.

Results showed large differences in reaction times for T—N similarity values categorized into low, medium, and high levels (P > F(205.85) = 0.0001), A Student-Newman-Keuls (SNK) Test of class means revealed that the mean reaction times for these levels differed significantly from one another, and that as T—N similarity increased, reaction times increased (Figure 5). Differences in reaction times for N—N similarity values were not significant (P > F(0.81) = 0.4483); an SNK test of class means for categorized levels of this variable showed that none of the levels differed significantly from any of the others (Figure 6). Set size (P>F(60,52) = 0.0001) and target colour (I)>F(70.33) = 0.0001) also significantly affected subjects' search times, A SNK test of class means for set size showed that all set sizes were significantly different from one another, indicating that the number of counties (or non-targets) on the map significantly affected search times (Table 2). An SNK test of class means for target colour suggested that subjects found some target colours, such as red and yellow, significantly easier to detect than the other target colours. N—N similarity x Target colour was the only interaction effect that significantly affected search times (P>F(7.58) = 0.0001), suggesting that some colours were more salient than others for different levels of N—N similarity.

Regression Analysis

A regression analysis using reaction time as the dependent variable and T—N similarity and set size as independent variables provided information about search patterns across the search surface. Results of this analysis indicated that regressing reaction time against set size for T—N similarity yielded search slopes (changes in reaction time as a function of set size) that were significantly different from zero, suggesting subjects were using a serial search process (P> F(37.40) = 0.0001). Furthermore, these search slopes were *not* significantly different from one another (P>F(0,18) = 0.8393), indicating that the *rate* of search was the same for all levels of T—N similarity, regardless of set size (Figure 7). A comparison of intercepts for the three slope equations indicated that as similarity increased by level, searches became significantly harder (P> r(43.03) = 0.0001), further corroborating the results of the ANOVA.

Table 1. ANOVA results for mean reaction times.

Dependent Variable: RT ($R^2 = 0.90$)	
T–N Similarity	PR > F (205.85) = 0.0001
N–N Similarity	PR > F (0.81) = 0.4483
Set Size	PR > F (60.52) = 0.0001
Target Colour	PR > F (70.33) = 0.0001
T–N Similarity × N–N Similarity	PR > F (2.21) = 0.0905
T–N Similarity × Target Colour	PR > F (1.58) = 0.1478
N–N Similarity × Target Colour	PR > F (7.58) = 0.0001
T–N Similarity × Set Size	PR > F (0.31) = 0.9279
N–N Similarity × Set Size	PR > F (0.37) = 0.8943
Set Size × Target Colour	PR > F (1.61) = 0.0551

Set Size	Mean RT
9-County Map	596.52
17-County Map	683.55
25-County Map	726.82
33-County Map	801.30

Table 2. Mean reaction time (msecs) for set size.

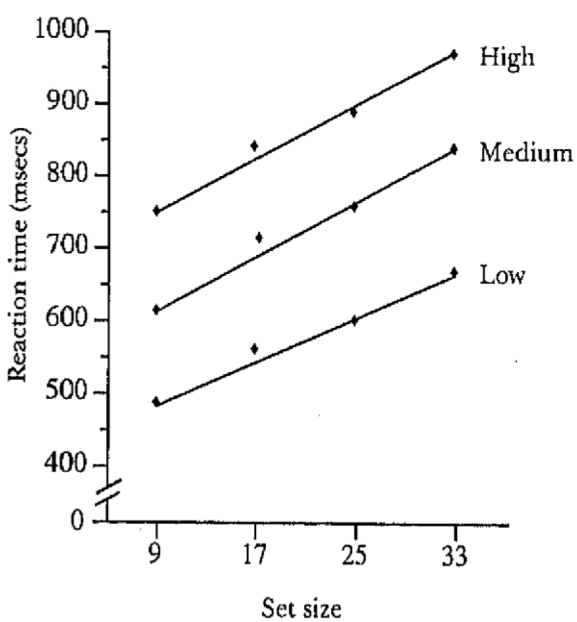


Figure 7. Regression results for T–N similarity with reaction time as the dependent variable.

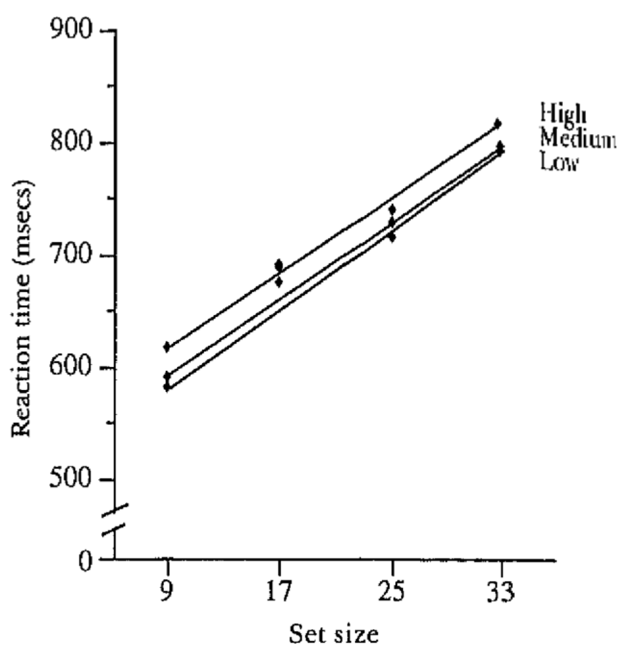


Figure 8. Regression results for N–N similarity with reaction time as the dependent variable.

A second analysis, in which N—N similarity and set site were the independent variables and reaction time was the dependent variable, produced similar results (Figure 8) Search slopes were again, significantly different horn zero, suggesting that subjects were using a serial search process ($P > F(24.04) = 0.0001$). These search slopes were also not significantly different from one another ($P > F(0.12) = 0.8849$), suggesting that the *rate* of search was the same for all levels of N—N similarity, regardless of set size. A comparison of intercepts for these three slope equations, however, indicated that as similarity decreased by level, searches did *not* become significantly harder ($P > F(0.13) = 0.8789$), again verifying the ANOVA results.

Discussion

In this study, a number of factors influenced the search efficiency of subjects interacting with bivariate cloropleth maps. Target colour, set size (the number of counties on the map), and the similarity of the target colour to the non-target colours on the map (T—N similarity) all significantly affected subjects' response times for the target detection task. The significance of target colour as an in, dependent variable indicated that subjects detected n:(1 and yellow with much greater ease than the other legend colours, regardless of the similarity attributes of the mop. One possible explanation for this stems from Opponent Process Theory (Hering, 1964), which proposes four primary colours: red, blue, green, and yellow. These primary colours are perceptually unique; they are not mixtures of any other colours. In this sense, then, primary colours are extremes, and all other colours, created by mixing two or more primaries together, are located between these extremes (Hurvich, 1957; Eastman, 1986). Thus, it seems quite possible that primary colours may `pop-out,' reducing search times, whereas colours that are mixtures of primaries are perhaps located less efficiently. Brennan and Lloyd's study (1993), which examined the search processes used in detecting coloured boundaries, provided evidence to support this hypothesis. Such an explanation, however, does not address the question of why the greens in the legend did not behave in a similar manner. Perhaps the effect was reduced in this instance because subjects had to process two variations of green. Another plausible explanation comes from further results of the Brennan and Lloyd (1993) study. They found that differences in colour aided the search process, with brighter, more saturated target colours increasing the efficiency of the search task. A similar effect could have occurred in this study, since the red and yellow colours used were highly saturated, whereas the other colours in the legend were more muted in appearance.

Set size also moderated search efficiency, indicating that searches were at least partially serial in nature; had they been strictly parallel, reaction times would have been independent of the number of counties on the map. Although set size was a significant variable in the ANOVA, results of the regression analyses indicated that it did not play a role in moderating search efficiency. Rather, increases in set size caused *consistent* increases in reaction times across the entire search surface. Such behavior eliminates this variable as a possible factor in moderating search efficiency.

As initially predicted, search times became significantly longer as the target colour came closer to matching the non-target colours. Furthermore, regressing subject reaction times against set size for T—N similarity levels suggested the following:

1) in completing the search task, subjects most likely used a serial search process;

2) the search task became significantly harder as T-N similarity increased; and

3) reaction times increased with set size, but this increase was consistent across the surface.

For N-N similarity, the differences in search times for individual levels proved not to be significant. Contrary, then, to the original hypothesis, search tasks across N—N levels appeared to be equally difficult, rather than becoming harder as N-N similarity decreased. As with T—N similarity, regression results showed that searches were most likely serial processes, and that changes in reaction time as a function of set size represented a consistent change over the search surface.

Why didn't N-N similarity levels affect the search process in the manner predicted by Attentional Engagement Theory? One clue points to the search surface itself. Duncan and Humphreys (1989, 1992) never quantitatively defined this surface in their work. The fact that Sector 9 conditions could not be represented on maps obviously affected the mean reaction time for the lowest level of N-N similarity. Had maps existed for that sector, it seems quite probable that subject reaction times for that level, given the general trend of search times found across the search surface, would have risen considerably (Figure 10). Another possible cause sterns from the significant interaction of target colour and N-N similarity. Ideally, each level of N-N similarity would have been represented by maps in which all target colours were used equally, thereby limiting the effect of target colour on search times. Due to an artifact in the experimental design, however, maps representing each of the levels used varying numbers of target colours, This imbalance could have affected search times across the different similarity levels.

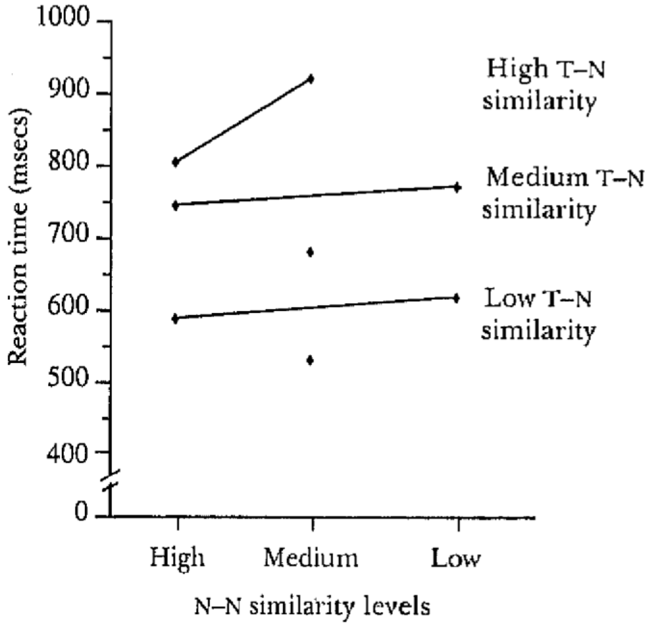


Figure 9. Regression results for interaction of T–N and N–N similarity levels.

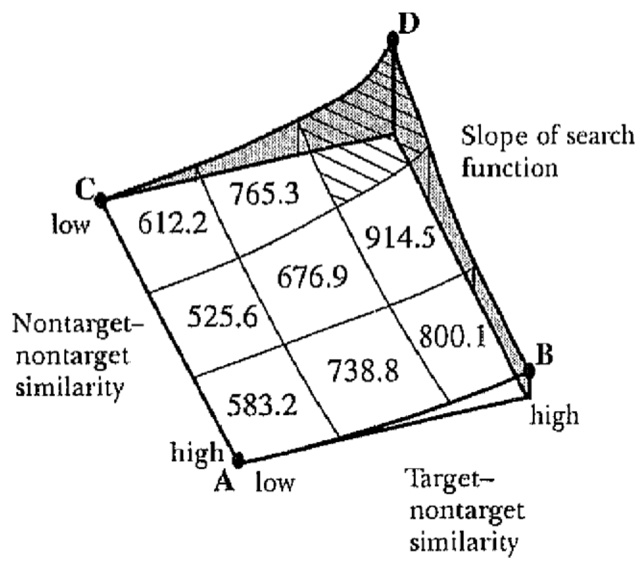


Figure 10. Mean reaction times for individual sectors.

The interaction of T—N similarity × N—N similarity also did not significantly affect search times. A plot of this effect indicated that the impact of T-N similarity on search times, contrary to expectations, was relatively constant across levels of N-N similarity (Figure 9). Thus, it appears that the most important attribute affecting the efficiency of the visual search process, at least for this study, is T-N similarity. Despite the lack of a significant T-N × N-N interaction, however; the nature of the search surface conforms to that predicted by Attentional Engagement Theory. By mapping the mean reaction times for each sector over the search surface, one can see that, as the search surface is traversed diagonally from lower left to upper right, search efficiency varies continuously and with a general decreasing trend (Figure 10).

Conclusions

Results of this study showed that the attribute of similarity significantly affected the efficiency of the visual search process used for bivariate choropleth maps. Attentional Engagement Theory, however, cannot be conclusively supported as a model for this search process because only one of the similarity attributes, T—N similarity, was found to affect the search task significantly. The general trend of the search surface conforms to the predictions made by Attentional Engagement Theory; however, the fact that *N—N* similarity did not play a significant role in moderating search efficiency precludes full acceptance of the theory.

Perhaps the most important information gleaned from this research is that T—N similarity appears to be much more important than *N—N* similarity when searching for colour areas in a map environment. Further research is needed, however, before cartographers can dismiss either the importance of N—N similarity to the map-reading process or the viability of Attentional Engagement Theory as a potential model for cartographic search processes. For instance, quantification of the search surface should be explored in more detail, especially since the absence of Sector 9 has such a serious impact on the behavior of similarity. Also important to this study was the selection and definition of colours; since the search surface was defined by these qualities, perhaps further studies are needed to examine colours for bivariate choropleth maps in more detail, Other avenues of research that would add to the knowledge base of visual search processes used in cartography include extending the work done in this study to determine if these findings can be extrapolated to other visual variables, and conducting other comparative studies of visual search models in a cartographic context.

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Resume La detection de la couleur sur des cartes statistiques bivariables : le processus de recherche visuelle La recherche est une tache fondamentale, mail complexe dans le processus de lecture de carte. Certains psychologues ont explore le role de Ia recherche visuelle dans in connaissance, at its ant propose nombre de modeles qui puissent offrir aux cartographer une base pour comprendre comment les gees cherchent une information cartographique specifique. Le but de cette recherche etait d'exarniner le processus de recherche visuelle utilise par des utilisateurs de cartes losqu'ils travaillent sur des cartes statistiques bivariables et d'evaluer le potential d'un *des* modeles de la psychologie, la Theorie de l'engagement attentionnel, pour expliquer ce processus. Lamle a utilise une Cache de recherche normale qui a determine l'efficacite du processus de recherche en amenant les sujets a rechercher sur une carte des couleurs ciblees parmi des couleurs non ciblees. tine analyse des temps de reaction a montre que refficaci Le de la recherche a *ate* affectee par les variables sulvantes : la couleur ciblee, le nombre total d'objets sur la carte, et la similarite de in couleur ciblee avec les autres couleurs non ciblees sur Ia carte.

Zusammenfassung Die Ansprache von Farben in bivariaten Flachenkartogrammen: der visuelle Suchprozell Suchen ist eine fundamentals, aber komplexe Aufgabe im ProzeB des Kartenlesens. Mehrere Psychologen haben die Rolle der visuellen Suche in der Kognition erforscht, und sie habeas eine Anzahl von Modellen vorgelegt, mit deren Hilfe Kartographen verstehen konnen, wie man in einer Karte nach spezifischer Information sucht. Die vorliegende Studie hate einmal den Zweck, den visuellen Suchproze0 beim Lesen bivariater Flachenkartogramme zu untersuchen. Weiterhin saute bewertet werden, wieweit die Theorie der Aufrnerksamkeitserregung¯, eins der Modelle aus der Psychologie, diesen ProzeB zu erklaren hilft. Die Wirksamkeit des Suchprozesses wurde mit Hilfe einer Standard-Suchaufgabe hestimmt: die Versuchspersonen muBten, aber den Kartenspiegel hin, Zielfarben ansprechen, die verstreut zwischen Nicht-Zielfarben vorkamen. Eine Analyse der Reaktionszeiten zeigte, &A die folgenden Variablen die Wirksamkeit der Suche beeinfluBten: die Zielfarbe, die Gesamtzahl der kartierten Objekte und die Ahnlichkeit einer Zielfarbe mit NichtZielfarben.

Resumen Descubrimiento de Color en Mapas de Coropleta Bivariada el Proceso de la Busqueda Visual El proceso de busqueda as un trabajo fundamental pero complejo para leer mapas. Varios psicologos han explorado el rot de Ia busqueda visual en la cognition y altos han propuesto algunos modeles que tal vez puedan ofrecer a los cartografos una base para entender coma la gente busca informacion especffica en mapas. El proposito de este estudio fue el de examinar el proceso de bilsqueda visual usado por lectores de mapas cuando trabajan con mapas de coropleta bivariada y tambien para evaluar el potential del model° psicolegico llamado *La Teoria del Involucramiento Atencional* para explicar el proceso de b6squeda. El estudio emple6 una tarea de bfisqueda estandar, pidiendo a sujetos buscar colores especificos entre colores noespecificos a traves de un mapa, at cual determin6 la eficiencia del promo de busqueda visual. Un analisis de los tie mpos de reaction mostrO qua las siguientes variables afectaron a la eficiencia de la btisqueda: el color especffico, at Mimero total de objetos en el mapa y la similaridad del color especffico con los dernas colores no-especfficos en el mapa.