The effectiveness of dynamic graphics in revealing structure in multivariate data

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Previous work by the authors showed no significant benefit for dynamic graphical presentation as opposed to static scatterplots in determining the number of data clusters present in multidimensional data sets. In the present study, subjects interactively looked for different types of structure, such as linear trends, clusters, or increases in variance of one variable, rather than discriminating number of clusters, to more closely mimic actual exploratory data-analysis features of interest. Searching for structure failed to prove significant benefits for dynamic data presentation.

John Tukey, the pioneer of exploratory data analysis, saw the object of his inquiry to be "looking at data to see what it seems to say" (1977, p. v). Although the domain of statistical graphics has been explored since the time of Playfair (1786), some of the most directed and concerted efforts have been led by Tukey (1977; Tukey & Tukey, 1988), Cleveland and McGill (1984, 1986), Young, Kent, and Kuhfeld (1988), Young and Rheingans (1990), and Tufte (1983, 1990). A graph encodes information by attributes such as geometry, texture, and color. This information is decoded visually when we look at a graph, and this process of decoding is graphical perception (Cleveland, 1987). A visualization is successful only if the visual decoding is carried out accurately and efficiently.

Cleveland and McGill (1984) have developed a paradigm for studying graphical perception. They conducted a series of experiments to determine the set of elementary graphical perception tasks performed when one views a graph and to rate these tasks on the basis of the ability of an observer to accurately perform them. The tasks they identified, ordered from most to least accurate, include determining the following: position along a common scale, position along identical, nonaligned scales, length, angle/slope, area, volume, and color hue/color saturation/density.

Recently, the computer graphics community has brought its expertise to bear on graphical data display, expanding the available techniques and renaming the field "scientific visualization" (Becker & Cleveland, 1991b). Scientific visualization encompasses a variety of methods that were previously either not available or limited in scope. Factors such as animation, dynamics, color mapping, transparency, and stereography have provided techniques beyond the elementary graphical perception tasks initially investigated by Cleveland and his colleagues. The study of graphical perception needs to be expanded to examine the effectiveness of these new representational techniques,

as well as to determine which techniques are most effective for a given data set.

Toward this end, Marchak and Whitney (1990) compared the dynamic depiction of three-dimensional (3-D) data with traditional scatterplots, particularly with respect to the ability of observers to extract cluster information from multidimensional data sets. They found no significant difference between static and dynamic presentations in subjects' ability to determine the number of clusters present. One possible explanation for these findings was that the experimental conditions constrained the ability of subjects to interact with the data. Marchak and Marchak (1991) attempted to replicate the original findings and explore the effect of interactivity on dynamic presentation methods. Once again, no significant difference was found between static and dynamic presentations, nor was there a difference between interactive and passive presentation methods.

Figure 1. Structure type.

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Figure 2. Degree of structure.

Figure 3. Static scatterplot matrix.

Together, these findings suggested that, at least for data sets consisting of point clouds, little or no benefit is realized by adding interactive dynamic capabilities to data interpretation. It is possible that the task of determining the number of clusters present does not benefit from the addition of dynamic graphics. Perhaps a better task would consist of looking for the presence of structure in noisy data, because structure might be more evident when data are animated. Young, Kent, and Kuhfeld (1988) stated that dynamic graphics methods "capitalize on the pattern recognition power of human vision and the computational power of graphics workstations to help data analysts look for structure (form hypotheses) that may be hiding in their multivariate data" (p. 393).

The present study explores this possibility. Subjects interactively searched for different types of structure in point clouds, such as a linear trend, a cluster, and a "cone," as formed when the variance of one variable varies as a function of another, or for no structure (Figure 1). Furthermore, the objects varied in degree of structure, either high or low, with degree defined with respect to the variance of the spread of points making up the structure. The subjects' task was to identify the type of structure present, based on the above four categories. If dynamic graphics provide more information than a static scatterplot, subjects should be more accurate in identifying structures in the dynamic condition and better at detecting objects with a lower degree of structure.

METHOD

Subjects

Five engineers from TASC, all with normal or corrected-to-normal vision, served as volunteers.

Design

A $2 \times 4 \times 2$ within-subject design was used: two graphic representation techniques (dynamic vs. static), four structure types (cluster, linear, conic, and none), and two degrees of structure (low and high). Presentation order of representation techniques was balanced across subjects, whereas type and degree of structure was randomly distributed across trials.

Stimuli

For the linear, cluster, and cone conditions, each structure was made up of 100 points and embedded in a noise cloud made up of 200 random points. For the no-structure condition, 100 additional random points were added to the noise. All structures were equal in length, and orientation and offset from the origin of the 3-D display were randomly distributed across structure types.

Degree of structure was manipulated for each structure type. For the linear and conic structures, degree of structure varied with the

Figure 4. Mean number of errors versus structure type.

Figure 5. Interaction of presentation method and structure type.

ratio of the length of the structure to the standard deviation of the width of the distribution of points, with low and high values, respectively, of 1 and 5 for the linear structure and 1 and 3 for the conic structure. For the cluster, the radius of the cluster was varied, with a value of 1 for the low condition and 0.5 for the high condition (Figure 2).

Ninety-six 3-D data sets were generated, with 12 examples of each structure type crossed with each degree of structure.

Apparatus

For the dynamic condition, the stimuli were presented on a Macintosh SE computer using MacSpin, a dynamic graphical data-analysis package produced by D2 Software (see Donoho, Donoho, & Gasko, 1988). The stimuli were rotated about each of the three spatial axes by using the rotation functions provided by the software.

In the static condition, a scatterplot matrix (SPLOM) of all possible x , y , and z combinations was created for each of the 96 data sets (Figure 3). The plots were each printed on a separate sheet of paper and combined in a three-ring notebook.

Procedure

In the dynamic condition, the subjects were shown examples of each of the structure types, and each structure was rotated 360° about each of the three axes. The subjects were then shown the same structures embedded in a noise cloud of random points, also rotated around each axis. After being instructed on how to use the software, the subjects viewed the 96 stimuli for 15 sec each and were permitted to rotate the stimuli freely. They then indicated the structure type present in the display by recording on a response sheet L for linear, K for cone, C for cluster, or N for none.

In the static condition, the subjects were shown SPLOMs of each structure type, the SPLOMs displayed first alone and then embedded in noise. They then viewed each of the 96 stimuli for 15 sec and recorded their determination of structure type in the same manner as they did in the dynamic condition. The order of the conditions and the order of data set presentation were varied across subjects.

RESULTS AND DISCUSSION

A repeated measures analysis of variance was performed on the number of errors $\times$ presentation method, structure type, and degree of structure. For presentation method, there was a marginally significant difference [$F(1,4) = 6.71, p = .061$], with mean number of errors of 9.45 for the dynamic condition and 8.58 for the static presentation method. For structure type, $F(3,12) = 5.86, p = .011$, with mean number of errors of 9.15, 7.65, 8.45, and 10.80 for linear, conic, cluster, and no structure, respectively (Figure 4). There was no significant difference for degree of structure.

The interaction of presentation method and structure type was highly significant [$F(3,12) = 8.929, p = .002$]. Contrast tests showed a significant difference between dynamic and static presentation methods for cluster, conic, and no-structure conditions ($p = .027, .002$, and $.004$, respectively; see Figure 5). Although the presentation $\times$ degree of structure interaction was not significant, for the interaction between structure type and degree of structure, $F(3,12) = 5.49, p = .013$, with the conic high degree of structure condition having the fewest errors. A contrast test of number of errors of conic structure type versus a combination of linear, cluster, and no structure was significant ($p = .015$).

These findings follow the earlier work of Marchak and Whitney (1990) and Marchak and Marchak (1991), showing no real difference between static and dynamic presentation methods with respect to ability to detect structure in point-cloud data. In the static condition, the subjects made fewer errors in detecting linear and conic

structures and fewer errors in detecting structure when there was none. This is consistent with the preliminary findings of Marchak and Whitney (1990). The subjects did best with structures that were the most object-like, such as cones and lines, and less well with more amorphous structures such as clusters. Overall, the subjects made the most errors in detecting structure when there was none. This follows from Smith (1986), who showed that when little or no perceptual organization exists in a stimulus (e.g., random), subjects impose perceptual organization; when some organization is present, subjects perceive it and further emphasize it.

Taken together, these findings suggest that dynamic rotation does not provide a significant benefit in locating structure in 3-D data and, in fact, is marginally worse because it results in overreporting of structure not actually present in the data. Although such findings seem surprising, Becker and Cleveland (1991a) have stressed that scatterplot matrices can provide a large amount of information without the use of dynamic graphics. Furthermore, by combining such techniques as highlighting common data points across displays and selectively hiding and displaying points, it is possible to provide insights with scatterplot matrices that are equal to or better than those derived from rotation methods. However, it is conceivable that for other data-analysis tasks not involving point clouds, such as in volumetric rendering or colormapping, dynamic rotation may provide insights not possible in a static representation.

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