Performance and Saliency Analysis of Data from the Anomaly Detection Task Study

Adrienne Raglin[1] and Andre Harrison[2]

[1] U.S. Army Research Laboratory, Adelphi, MD. 20783, USA
{adrienne.j.raglin.civ, andre.v.harrison2.civ}@mail.mil

Abstract. Studies have shown that finding the changes and differences within a scene or image to detect important objects and areas of interest is a key skill for object detection, particularly for soldiers. These changes and differences can be considered anomalies within the content and context of the scene. The detection of anomalies can be seen as a data point related to different attributes to an individual's ability to detect key objects and areas. An Anomaly Detection Task (ADT) study conducting at the Army Research Laboratory (ARL) explored using this technique to investigate the relationship between individuals who were proficient in detecting targets. Initially, the multidimensional scaling (MDS) methodology was used to begin investigating similarities between the characteristics of these individuals. The findings of the MDS study showed some correlations between performance in the ADT and individuals that were considered proficient in object detection. During the analysis of the results from the study an additional research question was posed. The new question: Could using the ADT data aid the development of computational algorithms that would detect objects in images in the same manner that these individuals detected object related anomalies. To start this investigation the Ideal Observer Model (ioM) was selected as the algorithm. The ioM is a saliency based algorithm that incorporates how human visual processing focuses attention on important objects and features. We compared the results from the ioM to the results of the ADT study. If the findings show correlation this information can be used to fine tune the algorithm. This paper will present a summary of analysis of the results from (ADT) study and present sample results of the analysis of the ioM for comparison.

Keywords: Anomaly detection, multidimensional scaling, saliency, visual search

1 Introduction

Traditionally, applications of anomaly detection can be found being used in a variety of fields such as medicine, computer security, and communications. Object detection applications take advantage of the existence of anomalies as a technique to identify objects and areas that can be important within a scene [1]. In general, objects that deviate from their backgrounds are considered anomalous. Additionally, different elements of a scene can result in objects looking anomalous. The effects of environmental elements such as wind, smoke, and dust left on objects within a scene can cause those objects to appear anomalous. Visible features of objects, components of objects, and object placement can also be used to discriminate important objects from their background. These features can include shape, color, contrast, and texture. Therefore, the detection of anomalies can enable an individual to locate objects whose characteristics are distinct from their surroundings without apriori knowledge of the object type or location. The ability of individuals to notice these characteristics may aid in allowing them to find potential targets, obstacles, and hazards in multiple environments. For the sake of this discussion we will define these individuals as “anomaly detectors.”

Can individuals who have this ability be determined experimentally? An Anomaly Detection Task (ADT) study conducted at the Army Research Laboratory (ARL) explored using anomaly detection techniques in an object detection task to attempt to answer this question. Included in the ADT study additional performance, psychophysical, and background data was captured. The application of MDS technique to the datasets was used to address the challenge of identifying the attributes associated with these individuals. Then we applied the ideal observer model (ioM), a visual saliency algorithm, to see if the areas selected by the algorithm would be inline with those of the detected anomalies.

2 Anomaly Detection Task

The ADT focused on anomaly detection as a component of object detection. Software was developed to present images to participants to allow them to look for different anomalies. Scores were given based on the number of anomalies correctly detected. The same images were annotated by subject matter experts (SME) and served as ground truths.

In addition to the scores from the software, participants also performed a set of vision related tasks. The vision 100% task used the Ishihara plates. Each participant was asked if they could read the number behind the colorful dots from the different pseudochromatic plates. If a participant was unable to see the number they may suffer from red-green color blindness. The vision 2.5% used a standard low contrast sensitivity testing chart. It measures the smallest optotypes size a participant can recognize. This is also used to measure visual acuity at high contrast level. The depth acuity task used a device similar to the Howard-Dolman test to determine what was the smallest detectable depth difference for each participant. The device developed at ARL was used to extend this concept and capture measurement of unusual depth acuity. The minimum, maximum, and average scores were calculated. The depth acuity tests were used to determine if a participant could identify an object at given distances.

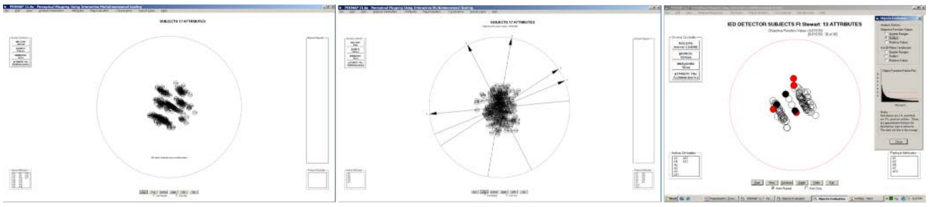
All of the vision tasks measured important parts of normal vision. An individual’s ability to distinguish an object from its surrounding when it may not have a clearly defined outline as well as distinguishing an object at a distance is essential for object detection. In addition to be able to discriminate subtle differences in color between an object and its background can be used by an individual to detect objects as well. These performance measures and basic demographic information on the experiences, occupation, and assessment of the individual's ability to find anomalies was used to analyze potential similarities and difference within the participants.

3 Multidimensional Scaling

Borg [2] defines multidimensional scaling (MDS) as a technique for analyzing similarity or dissimilarity within data sets. "MDS attempts to model such data as distances among points in a geometric space." In [3] it states, "There are a number of well-known techniques for visualizing data… but are usually limited to relatively small and low dimensional data sets." MDS can reduce data set complexity while maintaining explicit measurements of object (dis) similarities. This aggregation process explicitly complements other methodologies such as principal component analysis, which are less tolerant of incompleteness and variations in actual local implementation of test methods found in data sets typical of distributed personnel demographics and testing. The data from the ADT study is complex, with different data types, variation, taken from multiple sites and with potential incomplete data at different levels. Therefore, using MDS is one technique for addressing the complexities of this data.

The tool for this MDS analysis was Perceptual Mapping, PERMAP [4], a freeware program widely used, in part, due to its versatility in terms of the data input options, such as descriptive state vectors of attributes of differing data types. A perceptual map is a plane that conveys information about perceived relationships between objects. With this method, hidden structures possibly residing in the data set for identifying attributes of participants in the study may be uncovered. The data gathered during the ADT was reduced to a set of descriptive vectors; each vector was composed of 17 attributes listed in Appendix. The perceptual map of the MDS solution displays all 17 attributes in **Fig. 1**. The map shows the entities forming several reasonably defined groups. The basis of these groupings does not appear to be dominated by experimental site although further investigation is planned. This is important, as data collected from several sources may have a bias due to local implementation of the experimental protocol, individuals' occupations available at the site, specific training, etc.

Biplots were used to analyze the impact of "parking," or removing selected attributes from the study. The direction of steepest ascent, or gradient, provides important information in discerning the distribution of an attribute's values across a perceptual map. The gradient is indicated as a vector superimposed on the map that points in the direction that a particular attribute increases most rapidly. In the PERMAP software, standard least squares was used to find the best possible gradient vector. [5]. Displaying all active gradient vectors at once on the map helps determine which attributes are redundant and which are fundamentally different from one another. The ideal situation would be one in which all the attribute gradient vectors fall into two orthogonal groups. The 17 attribute data set was analyzed using the ratio type MDS and compared with the map generated using the interval type MDS displayed in **Fig. 1a**). The metric multidimensional scaling type generalizes the optimization procedure through minimizing of the stress function. **Fig. 1b**) is an example of the map for a set of parked attributes.



a.) **b.)** **c.)**

Fig. 1. PERMAP MDS model: a) multiple sites, 17 attributes b) experiential factors parked c) one site, 13 attributes, experts and outliers marked as red and black circles and respectively.

The general consensus is that MDS results should not be forced into a "Pass/Fail" situation depending on some particular value of some particular statistic. The results should have face value, that is, do they make sense to an untrained observer. Adequacy and interpretability should dominate the debate over the appropriateness of MDS results, and statistical measures must yield to meaningful interpretation [5] [6]. With that in mind, the preliminary results are presented. In **Fig. 1c**) data for one site was selected and the attributes were reduced to 13, with attributes 1, 3, 5, 7, and 10 parked. These results showed the participants from this site grouping in three clusters, experts and outliers highlighted as red and black circles respectively. The Shepard Plot for these results shows a reasonable fit to the data with an R^2 of .905. For these results selected ADT scores and experiential attributes dominated. In addition, there is indication that some of participants from this site have characteristics similar to those who designated as proficient.

4 Saliency Analysis

As work continues on analyzing the performance data from the ADT study we have begun investigating the data from the participants that were designated as experts or highly proficient. We would like to explore how algorithms in visual search also called visual saliency algorithms can be developed to automate the process of detecting targets based on the data from the ADT study. The identification of locations with unique or anomalous features in an image is an important element in all visual saliency models; models often differ in the approach taken to classify a feature as unique. By comparing the types of anomalies identified by experts vs. those identified by the saliency model we may be able to improve the detection of targets in an image. Models of visual saliency, especially bottom-up models typically operate in a three-step process as described by Feature Integration Theory [7]. First, an image is decomposed into the basic features that make up the image. These features are typically things like changes in color, changes in shape, and changes in the orientation of lines, 2nd locations with an anomalous or unique features or feature values are identified. Thirdly, each feature domain is combined to identify the most unique or anomalous locations within the images, hopefully containing the target location. This bottom-up process is well suited to predicting where people look in an unguided visual search task. The visual saliency model we used for comparison was the ideal observer model (ioM), which is a visual saliency model that predicts where a person will look in an image based upon how much information is present in each location within an image.

Using our SME data as ground truth we ran the ioM on images to see if there is overlap between areas highlighted by the IOM and annotated by the SME. We hope that some overlapping will occur potentially indicating links between the SME performance and the ioM bottom up processing of visual information algorithm. The results are shown in Fig. 1. The image on the left shows a scene with a red and blue polygon indicating areas of interest. The image on the right show the top 60 most salient areas identified by the ioM algorithm. In this sample image the area highlighted by the red polygon is marked as the most salient area and the area highlighted by the blue polygon is marked near the 55th most salient area. This example shows that it is possible for the ioM algorithm to find areas selected by the SME, it also shows the challenge that adapting the algorithm so that it replicates the selections of the SME is not a simple matter.

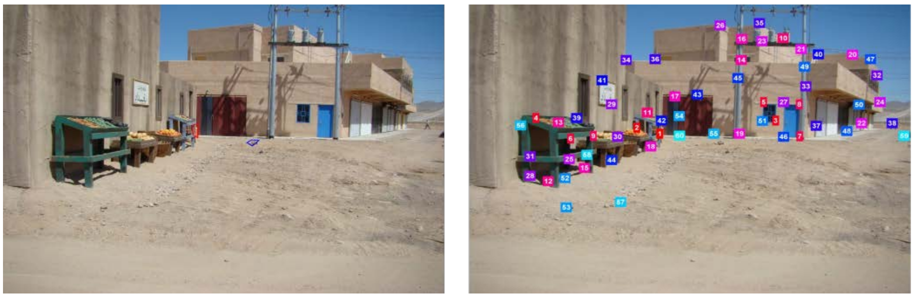


Fig. 2. The image on the left has objects of interest highlighted by the SME. The image on the right are the results from the ioM algorithm highlighting the top 20 most salient areas.

5 Conclusions

J. Martinez-Martinez et al. stated, “There are a number of well-known techniques for the visualization of data, … but they are usually limited to relatively small and low dimensional sets” [3]. MDS is one approach to visualizing high dimensional sets of data. The possibilities inherent in resemblance-based analysis and investigation into specifics have not been exhausted in this preliminary analysis. While it may seem to be ideal to isolate each attribute separately the relationships between attributes may be lost [8]. The conclusions stated here should be regarded as initial findings and explored further. For example, the effect of experimental site on the grouping.

This initial investigation into the data using MDS techniques has presented some useful insights that indicate possible correlation between individuals identified as SME and the remaining participants of the study. The initial analysis of the objects in the sample scene highlighted by SMEs with the results of the ioM analysis show potential correlation. We propose future work that explores how the data from the SME can be used to adapt the ioM algorithm to determine if we can get the algorithm to perform in a similar manner.

Acknowledgement goes to Ann Bornstein, former statistician at the US Army Research Laboratory. She and I worked on this project prior to her retirement. Her interest in the application of multidimensional scaling techniques to general data fusion problems prompted this analysis. Her contributions and expertise were extremely valuable.

Appendix:

Set of 17 attributes used in MDS Analysis

Attributes 1-6: Six scores for correctly identifying anomalies from image presented using AADT software. The AADT software was developed to present and score the images for the ADT task.

Attributes 7-8: Vision 100% and 2.5% test

Attributes 9-11: Min, Max, and Average Depth Acuity Score

Attributes 13-15: Yes/No responses to selected occupation and experience demographics questions

Attributes 16-17: results from object detection tests where objects were placed 5 and 10 meters from participants

References

1. Chandola, V., Banerjee, A., Kumar, V.: Anomaly Detection: A Survey. (2007).
2. Borg, I., Groenen, P.: Modern multidimensional scaling : theory and applications. Springer, New York (2005).
3. Martinez-Martinez, J., Escandell-Montero, P., Soria-Olivas, E., Martin-Guerrero, J., Serrano-Lopez, A.: A new visualization tool for data mining techniques. In: Progress in Artificial Intelligence. pp. 1–18 (2016).
4. PERceptual MAPping (PERMAP) Software.
5. Heady, R., Lucas, J.: MDS Analysis Using Permap 11.8. (2010).
6. Torgerson, W.: Multidimensional scaling of similarity. Psychometrika. 30, 379–393 (1965).
7. Treisman, A.M., Gelade, G.: A feature-integration theory of attention. Cogn. Psychol. 12, 97–136 (1980).
8. Everitt, B., Hothorn, T.: An Introduction to Applied Multivariate Analysis with R. Presented at the (2011).