Feature Extraction with the VLS Feature Analyst System

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ABSTRACT

The extraction of geospatial information from imagery data is generally a labor-intensive process. Automated tools that could assist analysts in this process would be of tremendous benefit for the production of geospatial data at the National Imagery and Mapping Agency (NIMA). This paper examines a system called Feature Analyst™, developed by Visual Learning Systems (VLS). Feature Analyst employs machine-learning techniques to address a range of image analysis and exploitation tasks. The performance evaluation consisted of a series of tests in which cartographers extracted a variety of geospatial features using both the Feature Analyst and manual methods. Objective data were collected on the timing and relative accuracy of the extraction of vegetation and double-line drains. In addition, the participants provided subjective feedback on the functionality and user interface. This paper reviews the objectives of this study, describes the design of the evaluation, and presents the performance results. The timing comparisons indicate that Feature Analyst reduces extraction time by a factor of 5 to 10 over small areas. By using Feature Analyst to develop automated feature extraction (AFE) models over a small training set and then applying the models to larger areas, extraction times could be reduced by several orders of magnitude.

INTRODUCTION

Advancements in the development of algorithms to support rapid extraction of feature data from imagery offer the possibility of reducing the cost and improving the efficiency of operational production of geospatial data at the National Imagery and Mapping Agency (NIMA). An important step in the transition of such algorithms is a careful assessment of the performance and value-added associated with each algorithm. Through NIMA's Automated Feature Extraction (AFE) Test and Evaluation program, a test bed has been established for the evaluation of Automated Feature Extraction (AFE) technology. A series of evaluations using this test bed environment have been conducted over a two-year period. The objective of these evaluations is not to assign a pass/fail grade for each candidate AFE algorithm, but rather to develop a deeper understanding of each algorithm's strengths and weaknesses. Specifically, these evaluations characterize algorithm performance and provide a clear and measurable roadmap for performance improvement. This paper focuses on the evaluation of the Visual Learning Systems' Feature Analyst software for extraction of vegetation and drainage features.

NIMA's AFE Test and Evaluation program tests AFE software through a six-phase process, the last of which, if successful, is technology insertion in a commercial platform. The six phases include Qualification, Verification, Preparation, Quantitative Analysis, Modifications and Enhancements, and Technology Insertion (Table 1).

In phase 1, Qualification, we investigate the algorithm to see if it is relevant to NIMA's mission. In phase 2, Verification, we test the algorithm over developer provided data sets to see if it indeed functions as advertised. If so we then move on to phase 3, Preparation. In this phase we prepare for phase 4, Quantitative Analysis. A weeklong test culminates the fourth phase, the Comprehensive Quantitative Analysis or phase 4. This phase starts with one day of training and practice. The analysts then conduct both manual and algorithm timed extractions on four datasets. This test compared Feature Analyst with a manual approach that is similar to how current operations are conducted. Feature Analyst proved to increase production over hand digitization, while at the same time achieving more accurate and consistent results. After phase 4 is completed, phase 5 ensues, Modifications and Enhancements. These are changes and improvements made to the system, based on concerns identified during phase 4. The last phase is phase 6, Technology Insertion. Once an algorithm has passed phases 1-5 it is ready for technology insertion into a commercial platform. For Feature Analyst that platform was ArcGIS™.

Table 1. NIMA's Six Phase AFE Evaluation Process.

Phase	Description
1. Qualification	**Is this system relevant to NIMA's missions?**
2. Verification	**Does the system operate as advertised?**
3. Preparation	**Planning for controlled, quantitative evaluation**
4. Quantitative Analysis	**Conduct controlled evaluation**
5. Modifications & Enhancements	**Based on feedback from evaluations, developer implements changes**
6. Technology Insertion	**System is ready for commercialization or insertion by other means**

FEATURE ANALYST SYSTEM

Presently, the labor cost of creating and maintaining geospatial features is the central bottleneck within the GIS industry. Feature Analyst, developed by Visual Learning Systems, Inc., addresses this logjam by using machine-learning algorithms to accelerate the feature extraction and image classification process. This semi-automated approach reduces labor costs on digitizing projects while maintaining or exceeding traditional levels of accuracy. Feature Analyst extends the functionality of existing commercial GIS workflow processes, and exists as extensions to ArcGIS™ 8 and ArcView™ 3.2 from ESRI, as well as an extension to ERDAS IMAGINE™ from Leica Geosystems.

Role of Machine Learning in Image Classification

There are two types of approaches for identifying features of interest in remotely sensed images: *manual* and *task-specific automated* approaches. The first involves the use of trained image analysts, who manually identify features of interest using various image-analysis tools. This approach falls short of meeting government and commercial sector needs for three key reasons: (1) the lack of available trained analysts; (2) the laborious, time-consuming nature of manual feature identification; and (3) the high labor costs involved. Because of these drawbacks, researchers since the 1970s have been attempting to *automate* the feature extraction process. This has traditionally been done by writing a task-specific computer program (Jain et al. 1984; McKeown et al. 1993). However, these programs take an exceedingly long time to develop, requiring expert programmers to spend weeks or months *explaining*, in computer code, visual clues that are often trivially obvious to the human eye. In addition, the resulting handcrafted programs are typically large, slow, and complex. Most importantly, they are operational only for the specific task for which they were designed, typically failing when given a slightly different problem such as a change in spatial resolution, image type, surface material, geographic area, or season. Developing such programs is complicated by the fact that user interest varies significantly. While some task-specific automated approaches have been successful, it is virtually impossible to create fully automated programs that will address all user needs for every possible future situation. Feature Analyst overcomes these shortcomings by using cutting-edge statistical and machine-learning algorithms to model the feature-recognition process, rather than explicitly writing a software program.

Feature Analyst Workflow

Feature Analyst provides a paradigm shift to automated feature extraction since it: (a) utilizes spectral, spatial, temporal, and ancillary information to model the feature extraction process, (b) provides the ability to remove clutter, (c) incorporates advanced machine learning techniques to provide unparalleled levels of accuracy, and (d) provides an exceedingly simple interface for feature extraction. Feature Analyst works by taking a small and simple set of training examples (i.e., sample features digitized by the user), learns from the examples, and classifies the remainder of the image. Figures 1-4 demonstrates the basic Feature Analyst process of extracting features. In this example, the feature of interest was a particular type of rooftop associated with a class of government residential housing. Figure 4 shows the results whereby 95% of the user-specified buildings in the image are found with little or no error.

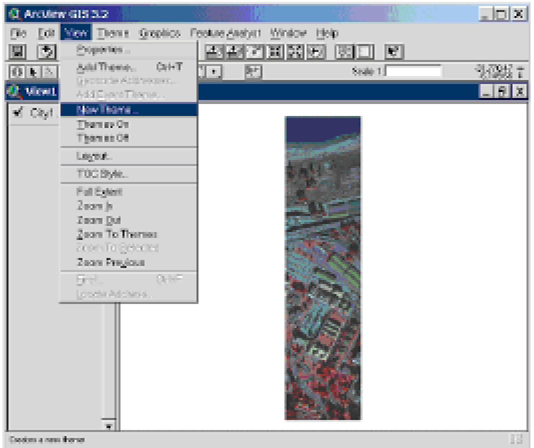

Figure 1. A sample of the original image. Four band color infrared, 0.5 meter ADAR. Source: Positive Systems, Inc. Location: Presidio in San Francisco, CA. Provided free of charge for research and publication

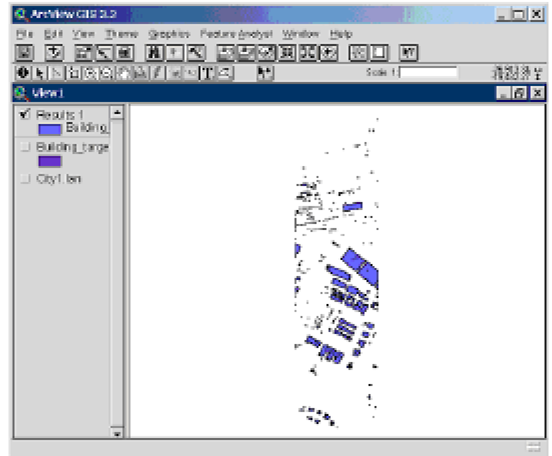

Figure 2. Results of the first pass of learning buildings.

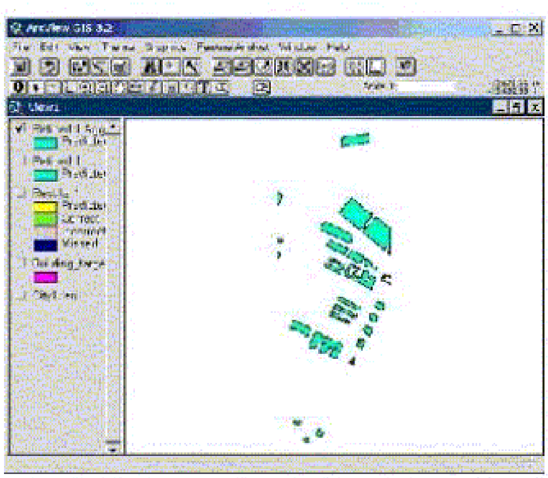

Figure 3. The user corrects the learner and resubmits to learning. Four band color infrared, 0.5 meter ADAR. Source: Positive Systems, Inc. Location: Presidio in San Francisco, CA. Provided free of charge for research and publication

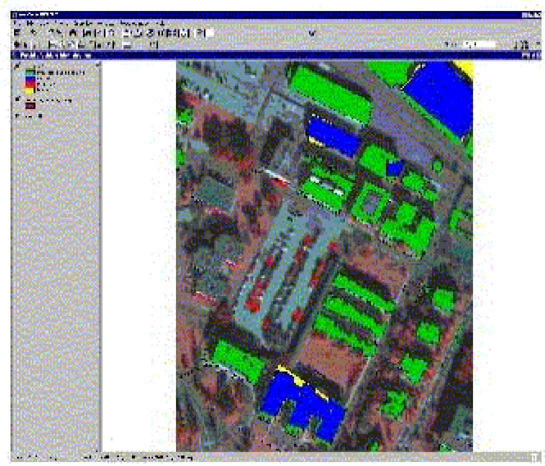

Figure 4. Results from the clutter mitigation pass of learning.

Value of Spatial Association

When classifying the contents of imagery, there are only a few attributes accessible to human interpreters. For any single set of imagery these are: Shape, Size, Color, Texture, Pattern, Shadow, and Association (Caylor, 1998). Traditional image processing techniques incorporate only color (spectral signature) and perhaps texture or pattern into an involved expert workflow process; Feature Analyst incorporates all these attributes, behind the scenes, with its Learning Agents. Figures 5-7 show the value of using these visual attributes, such as spatial association, in feature extraction. Figure 5 is the sample image. In this case, we want to extract white lines on airport runways. Using only spectral information, the best an analyst can do is shown in Figure 6; all materials with similar reflectance are extracted. Figure 7 shows the

Feature Analyst using a "square 7x7" input window. In this case, one needs to know the neighboring pixels are pavement or grass when extracting lines. This example illustrates the need to take into account spatial information when conducting true feature extraction.

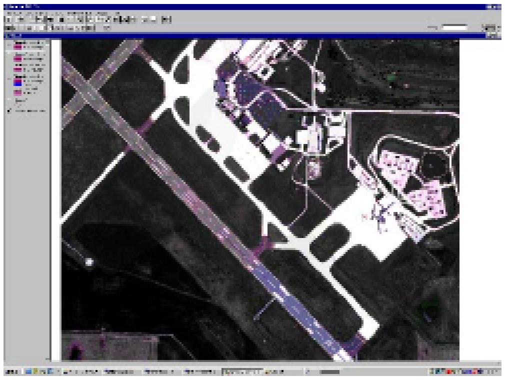

Figure 5. A sample of the original image. Four band color infrared, 0.5 meter ADAR. Source: Positive Systems, Inc. Location: Airport in Indiana. Provided free of charge for research and publication

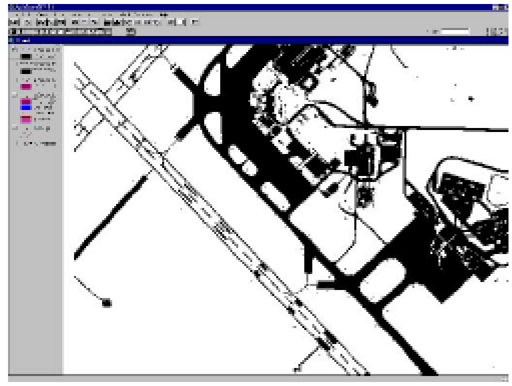

Figure 6. A sample of the original image.

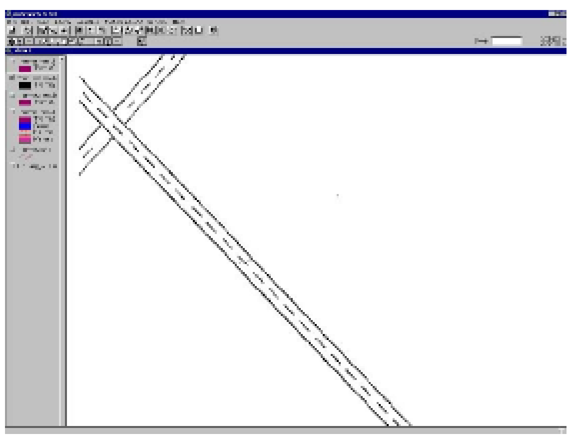

Figure 7: Feature Analyst classification using both spatial association and spectral properties.

Feature Analyst leverages the natural ability of humans to recognize objects in complex scenes and does not require the user to *explain* the human-visual process in an algorithmic form. Since the system does not require programming knowledge, users with little computational knowledge can effectively create automated feature extraction (AFE) models for the tasks under consideration. Feature Analyst offers three levels of automation with its AFE models:

1. The analyst quickly creates a small training set, explicitly sets up the learning parameters (such as the spatial association settings), and creates an AFE model. This AFE model is then applied to the remainder of the image.
2. The analyst creates an AFE model via a training set as in the above approach; however, the learning settings are generated automatically through the enterprise-wide sharing of AFE models. Thus AFE approaches and techniques can be shared and then fine-tuned, with a few training examples, for a particular feature extraction problem.
3. The analyst *batch* classifies a set of imagery with an existing AFE model (or set of models). This is full automation where features are extracted without human interaction.

In addition to automating the extraction of single features, Feature Analyst offers many tools for easily creating multi-class extractions (i.e., image classification). For instance, an analyst can segment an image into numerous classes (e.g., water, low-vegetation, high-vegetation, and structure). Additional capabilities of Feature Analyst include change detection, 3D feature extraction, data fusion, unsupervised classification, and advanced clean-up and post-processing tools (such as convert to line).

DESIGN OF THE EVALUATION

The approach employed in NIMA's AFE evaluations is comparison of feature extraction using the system under evaluation and a baseline system. Using the baseline system, analysts performed a manual feature extraction process that emulates current methods for production of geospatial data. ArcGIS™ was the baseline extraction system selected for this evaluation. The same analysts also performed the feature extraction tasks using the Feature Analyst system. For the purpose of this evaluation, the cost of constructing a feature database is assumed to be proportional to the amount of manual labor required to extract the desired features in accordance with the specification required for standard geospatial products. The primary measure of performance is the total time expended by an analyst to extract the features to the required level of accuracy. During the evaluation, experienced NIMA analysts verify the accuracy of the extraction. Features that do not meet specification are edited to bring them into compliance and the editing time is included in the total time for extraction.

The evaluation process began with analyst training in the use of the Feature Analyst and ArcGIS™. Following the training, the analysts had practice sessions with both systems to insure they were proficient in feature extraction before collecting actual performance data. All training and practice sessions used imagery that was not part of the actual evaluation. To verify that the analysts had achieved a sufficient level of proficiency, each analyst performed two successive timed extractions using the same data set. A large difference in the two times would indicate that the analyst was still on the steep part of the learning curve and more practice was warranted. Conversely, a small difference in the two times indicates that the analyst has achieved a constant level of proficiency and is ready to move ahead with the formal evaluation.

Table 2. Experimental Design for the Feature Analyst Assessment

Analyst	First Session	Second Session
Team 1 /Analyst 1	Feature Analyst	ArcGIS
Team 1 /Analyst 2	Feature Analyst	ArcGIS
Team 2 /Analyst 1	ArcGIS	Feature Analyst
Team 2 /Analyst 2	ArcGIS	Feature Analyst

In the formal evaluation, analysts extracted features from the test imagery under two sets of conditions: manual extraction using ArcGIS™ and assisted extraction using Feature Analyst. Thus, each image processed twice by each analyst – once manually and once with assistance. Because analysts become familiar with an image, a learning effect can cause an improvement in extraction time during the second session. To control for this learning effect, the sequence of processing was counterbalanced (see Table 2).

ANALYSIS AND RESULTS

The objective of data analysis is to quantify the performance difference associated with the feature extraction using Feature Analyst compared to the baseline (manual) process. The basis for the comparison includes the geometric accuracy of the extracted features (where is it located geospatially), the topological accuracy (number, placement, and connectivity of vertices), and the time required to extract the desired features. Assessment of the geospatial and topological accuracy consisted primarily of verifying that the extraction met the quality standard established by experienced NIMA analysts. If an extracted feature did not meet that standard, the feature was either edited or re-extracted. Once the extractions satisfied the required level of accuracy, the measure of performance is the total analyst time required for extraction, including any editing needed to satisfy the product specification. The data analysis progressed through four stages:

1. Verification of data quality
2. Assessment of learning effects and their bearing on the results
3. Comparison of performance using Feature Analyst compared to the fully manual process
4. Characterization of performance relative to the feature type

The verification of the data quality began with a review of the individual observations to identify any anomalous or atypical points. Correlation analysis and graphical techniques verified the consistency across the four analysts. In addition, statistical analysis revealed no outliers or other anomalous observations. The assessment of the sequential timed extractions at the end of the practice period demonstrated that all of the participants had achieved reasonable proficiency with Feature Analyst and ArcGIS™.

The heart of the evaluation is the comparison of extraction times using Feature Analyst and ArcGIS™. In the aggregate, extraction using Feature Analyst was nearly five times faster than using ArcGIS™ (Figure 8). Although the primary measure of performance is the analyst's time, it is useful to note that the processing time required by Feature Analyst is small. For the scenes used in this evaluation, processing time was less than half a minute per scene on average.

An analysis of variance (ANOVA) was performed on the total extraction times. The ANOVA demonstrates that these differences are real, and not due to chance (Table 3). This statistical procedure is a method for testing the difference of interest, manual extraction vs. Feature Analyst, while controlling for the effects of the individual analyst and the scene. The results show that, while controlling for analyst and scene, the difference in performance due to the system (manual extraction vs. Feature Analyst) is statistically significant. The significant interaction term (system by scene) arises because the analysts spent relatively more time editing the Feature Analyst results for scene one than for the other three scenes. For this one scene, however, total extraction time using Feature Analyst was still better than manual extraction by a factor of two.

In terms of accuracy, the experienced NIMA analysts judged the Feature Analyst results to be of generally high quality. Two particular results are worth noting (figure 9): (1) Because Feature Analyst classifies each pixel in the image, it has the potential of providing highly accurate boundaries for complex features such as land cover; and (2) The classification results are generally more stable than manual extractions by multiple analysts.

Table 3. Analysis of Variance for Extraction Time

Source	Sum of Squares	Deg. of Freedom	Mean Square	F-statistic	Significance Level
System	14398.3	1	14398.34	11.30	0.0437
Scene	5826.1	3	1942.03	1.52	0.3687
Analyst	312.0	3	103.99	1.28	0.3056
System by Scene	3822.1	3	1274.05	15.74	0.0000
Error	1699.9	21	80.95		

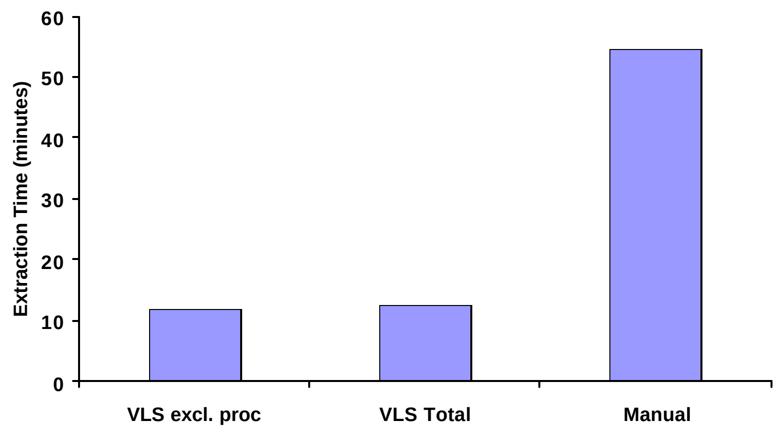

Figure 8. Overall Extraction Time for VLS Feature Analyst and the Manual Extraction Using ArcGIS™ System

One of the strengths of the Feature Analyst system is the ability to develop an AFE model over a relatively small training set and apply it to a larger area. If the training region is selected with care, the model will extend across the larger region with little or no degradation in performance. To test this idea, Feature Analyst was run over a full IKONOS scene for one of the land cover tasks and one of the drainage tasks. The results were presented to the four analysts, who were then asked to rate the quality of the results over the larger area and the implications for operational production using this capability. Universally, the analysts agreed that the accuracy of the feature extraction over the large region was comparable to the smaller scenes used in testing. If this approach were applied in an operational setting, it could dramatically reduce the analyst's workload (Figure 10).

The final step in the evaluation was to elicit subjective feedback about Feature Analyst from the participants. Two methods for obtaining this feedback are the post-evaluation discussions and a formal questionnaire completed by each of the participants. Both the questionnaire and the discussions revealed a high level of enthusiasm for the Feature Analyst system. Analysts agreed that the system was easy to learn and easy to use. The results for both landcover and drainage were impressive, demonstrating both good accuracy and substantial time savings compared to manual extraction methods. In short, the participants felts that Feature Analyst could make their jobs much easier (Figure 11).

CONCLUSIONS

This evaluation of the VLS Feature Analyst system shows substantial benefits for the development of geospatial data from imagery. The extraction of landcover and drainage features from commercial satellite imagery was performed approximately five times faster with Feature Analyst than with a standard manual extraction system (ArcGIS™). While the objective testing concentrated on relatively small scenes, a review of Feature Analyst's performance over larger regions suggests that the potential time savings in a production setting could be as much as a factor of 100, depending on the homogeneity of the region. Subjective feedback regard Feature Analyst is also very favorable -- participants indicated that Feature Analyst would be of great benefit in an operational environment.

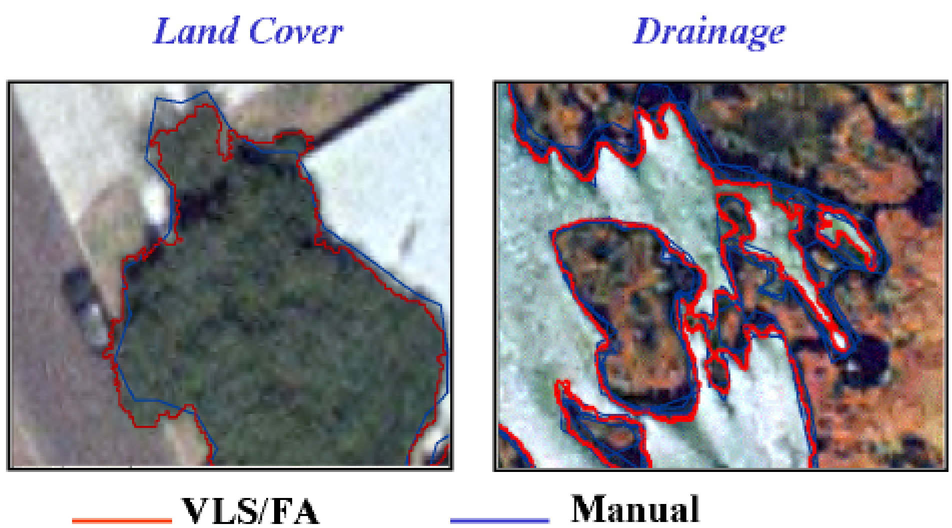

Figure 9. Illustrative Feature Extractions Using the Two Systems. Image on left is color (3-band), 6 inch aerial over Orlando, FL; provided free of charge. Image on right is color infrared orthophoto, DOQQ. Location: NE quadrant of Bayou Sauveur Quadrangle, LA. Available free of charge from the Louisiana Oil Spill Coordinator's Office.

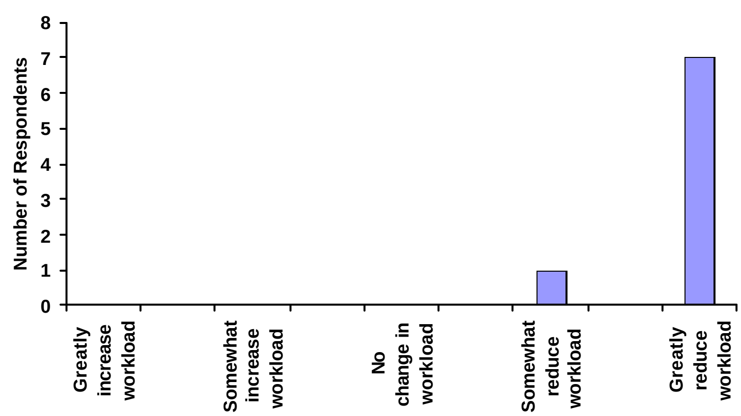

Figure 10. Analysts' Ratings for Application VLS Fe ature Analyst over a Large Region: Considering the use of Feature Analyst in an operational setting, how would the performance shown in this larger scene affect the analyst's workload, compared to manual feature extraction?

Acknowledgements

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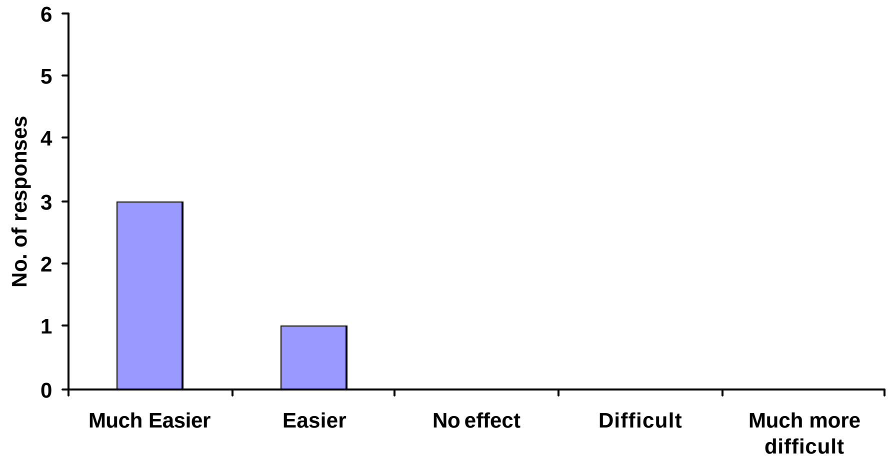

Figure 11. Overall Rating: If VLS Feature Analyst were available in you environment, it would make your job (circle one):

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