

Information Fusion for Feature Extraction and the Development of Geospatial Information

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Abstract - Numerous military missions require timely, accurate geospatial intelligence, yet the extraction of geospatial information from imagery data is generally a labor-intensive process. Automated tools to assist analysts in this process would be of tremendous benefit for the production of geospatial intelligence at the National Geospatial-Intelligence Agency (NGA). Methods that rely on data from a single image, while useful, generally fall short of producing useable geospatial products. Fusion-based methods which jointly process and exploit information from multiple sources offer ways to address many of the limitations of single-source analysis. This paper discusses the needs for geospatial intelligence and examines the benefits of fusion to address these needs. Results from several recent studies demonstrate the value added from a number of tools for automated data extraction (ADE). Experience gleaned from these studies also indicates several areas where new research and development is needed. The paper concludes with a brief discussion of future directions.

Keywords: Feature extraction, geospatial intelligence, evaluation, fusion

1. Introduction

The National Geospatial-intelligence Agency (NGA) has a mission to produce timely, accurate geospatial intelligence to support national and military requirements. Automated Data Extraction (ADE) technology offers a possible avenue to more timely and cost-effective production of geospatial information [1]. NGA's Synergistic Targeting Auto-extraction and Registration (STAR) Program is responsible for the development, evaluation, and transition of promising ADE technology. This paper examines fusion-based ADE methods, assesses the benefits of several new techniques, and identifies opportunities for future improvements.

The ADE methods of interest correspond to Level 0 (signals) and Level 1 (objects) fusion [2, 3]. The data includes multiple images from the same modality, multiple images from different modalities, and combining imagery with non-

image geospatial data, such as a digital elevation model (DEM). This paper addresses the quantitative and qualitative testing to characterize the performance benefits and limitations of several fusion-based ADE tools, relative to current baseline methods. This test corresponds to Phase 4 of the Test and Evaluation process described below and follows the standard approach employed by the NGA STAR Program [4-7]. A significant finding from recent evaluations is the need for enhanced post-processing and editing capabilities to "clean up" the results of automated processing.

2. Requirements for Geospatial Information

Accurate, timely geospatial information is critical for many military missions, such as intelligence preparation of the battlefield (IPB), mission planning and rehearsal, target development, and situational awareness. The geospatial information provides the foundation for planning, executing, and assessing military operations. To illustrate, consider the IPB mission. IPB is the systematic, continuous process of analyzing the threat and environment in a specific geographic area to support military operations [10]. It addresses terrain, weather, and the enemy, integrating enemy doctrine and mission to evaluate enemy capabilities, vulnerabilities, and probable courses of action. In practice, IPB is a 4-step process:

- [1] Define the battlefield environment -- characteristics which influence friendly and threat operations
- [2] Describe the battlefield's effects -- limitations and opportunities within the environment
- [3] Evaluate the threat -- determine how the threat normal conducts combat operations
- [4] Determine threat courses of action (COAs) - integrate the previous steps into meaningful conclusions

Geospatial data provides the information needed for steps one and two, driving the IPB analysis at all levels. Similarly, other military missions also rely on geospatial intelligence. NGA's STAR Program fosters the development and transition of tools needed to support these missions.

3. The NGA STAR Program

The STAR Program addresses the automated and semi-automated extraction of information from imaging sensor data. Areas of interest include feature extraction for production of geo-spatial information, automated/aided target detection and recognition, change detection, automated image registration, and imagery and information fusion to support each of these areas. The program consists of three elements:

- [1] Develop and Evaluate: Promote development of new tools and technology to support the efficient and effective exploitation of sensor data for production of accurate, timely geospatial intelligence. Test and evaluation provides feedback to developers and guides NGA technology investments
- [2] Prototype: Produce prototype tools and capabilities to address current and future needs and assess prototypes to foster system enhancement and transition
- [3] Commercialize: Assist in the commercialization of promising tools and technology

Although production of geospatial intelligence involves a number of tasks, the remainder of this paper will consider only feature extraction. The performance evaluation results presented for various systems compare the analyst's time required to extract the features using the ADE tool and the time required to extract the same features manually using standard tools. In both

cases, the extraction must satisfy standard product specifications. The analyst edited the initial extraction results as needed to insure that specifications were met and this editing time was included in the total extraction time.

The geospatial features of primary interest are roads, buildings, landcover (forests, agriculture, etc.), and drains (rivers, lakes and other water bodies). Extraction of a feature from imagery requires delineation of the feature, accurate geolocation of the feature with respect to the reference datum, and attribution of the feature. Most ADE tools have concentrated on feature delineation. Feature geolocation depends on the accurate registration of the imagery. Feature attribution provides additional characterization of features:

- Geometric properties such as road width, number of lanes, building height, river depth
- Material properties: examples include road surface (asphalt, concrete, gravel), river bottom (sand, rock)
- Use: For cultural features, how they are used. For example, is the airport is military, civilian, mixed, abandoned, under construction?

4. Role of Image Fusion

Single image sources provide limited information about important geospatial features. Feature extraction from a single data source is restricted to 2-dimensional information. The feature delineation is affected by viewing geometry and obscuration and panchromatic data provides very limited information about material properties. Image fusion, coupled with semi-automated extraction tools, can address the needs of the warfighter by overcoming many of these limitations (table 1).

Table 1. Applications of Fusion to Feature Extraction

Applications	Source Data	Example System	Comments
3-D roads and buildings	<ul style="list-style-type: none"> ▪ Stereo imagery ▪ Multi-look imagery 	USC Building Extraction System CMU Road Mapper	Multiple panchromatic images provide height information, minimize obscuration, shadow effect
Landcover, drains	<ul style="list-style-type: none"> ▪ Multi-modality imagery ▪ Multispectral imagery 	Neural Fusion GENIE Feature Analyst eCognition	Range of "machine learning" tools use spectral and spatial analysis to extract a variety of features
Feature attribution	<ul style="list-style-type: none"> ▪ Multispectral ▪ Hyperspectral 	eCognition TRULOCX	Reliance on spectral analysis to assess material properties
Drainage	Image and DTED®	DRAGON	Merges knowledge of topography with imagery

5. Systems Employing Fusion for Feature Extraction

5.1 Multi-view Extraction Methods

A common multi-source technique is to employ two or more images acquired at slightly different viewing geometries to perform a three-dimensional delineation of the features. The two images are from the same imaging modality, usually panchromatic images. For imagery collected at or near nadir, the footprint of the feature is evident in a single image and the parallax provides information about elevation. Two systems that use this approach are the Interactive Building Extraction System developed by the University of Southern California (USC) [6] and Road Mapper developed by Carnegie Mellon University (CMU) [8]. Both systems have been evaluated under the NGA STAR program and show performance benefits under certain conditions (figure 1). The USC system is particularly useful for extraction of complex buildings. As the right hand chart in figure 1 shows, using the USC method provides a significant reduction in

mean extraction time. The time savings is more pronounced for the images of Washington, DC, where the buildings being extracted are fairly complex.

The CMU system, in addition to performing a 3-D extraction of the road centerlines, estimates road width and road topology. The tests of the CMU system showed relatively little time savings for extraction of the road centerline. However, when road width is also extracted, the CMU Road Map tools showed real benefits compared to manual extraction using SOCET SET®. An interesting outcome of the test is that the CMU Road Map operating in “manual mode” was faster than in the “assisted mode.” Subsequent engineering analysis suggests that this difference is due in part to processing time associated with initiating the “seed” for the automated road tracking and recent improvements in the software are expected to reduce or eliminate this effect [8].

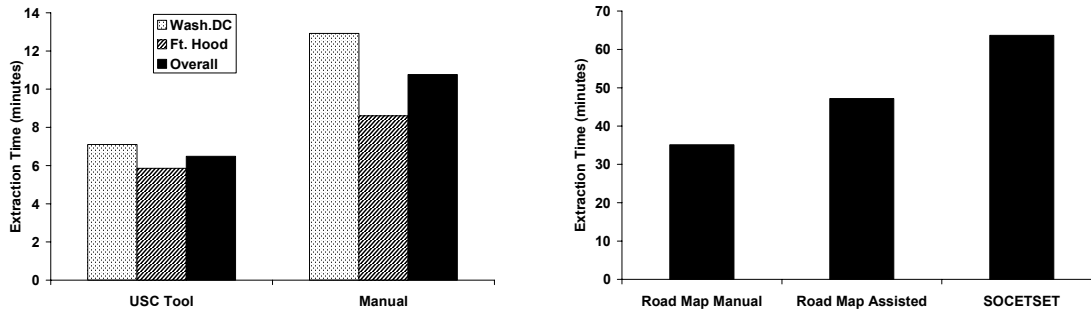


Figure 1. Extraction Times for Building Extraction (left) and Road Extraction (right)

5.2 Machine Learning Methods

A number of machine learning methods process a set of co-registered data layers to delineate features based on user guidance. The data layers could be multi-band imagery (such as multispectral or hyperspectral imagery) or images from different sensors that have been registered prior to exploitation. Although the precise processing steps differ from one system to another, the general approach is for the user to specify the feature(s) to be extracted either by identifying examples or specifying an initial rule. After viewing the initial extraction, the user can modify or refine the rules iteratively to improve performance. The final step is to manually edit the results to clean up any problems not handled

adequately by the ADE tool. The four systems evaluated to date under the NGA STAR Program differ in their approaches, strengths, and limitations (table 2). [5, 6, 7, 10]

The evaluation results indicate that each system holds promise for addressing elements of the feature extraction problem (figure 2). In all cases, the ADE tools show the greatest promise for extraction of irregularly shaped areal features, i.e., land cover and drains. When interpreting the timing data in figure 2, one should only compare the manual and assisted times within a system. Comparisons across systems are not meaningful for two reasons. First, each evaluation used different images and analysts. Second, the final products differed

across evaluations. In some cases, the ADE tool produced a full vector product and in other cases it produced a raster overlay of the feature.

Experience has shown that these features are difficult and time consuming to extract manually. In addition, there is substantial variability across analysts in terms of the accuracy and reproducibility of the manual extraction of these features – a problem that is greatly reduced through use of automated tools. Figure 3 illustrates the variability in manual extraction. The manual delineation performed

by four analysts, shown in blue, exhibits some variability. In addition, the polygonal regions do not precisely match the feature of interest. For the automated extraction, however, consistency and precision are excellent, as shown in red. Note that the automated extractions were also generated by four analysts, each marking different training exemplars to run the algorithm. This level of robustness and precision is one of the strengths of good ADE tools.

Table 2. Machine Learning Systems Evaluated Under the NGA STAR Program

Issue	eCognition	Feature Analyst	GENIE	Neural Fusion
Developer	Definiens Imaging	Visual Learning Systems	Los Alamos National Laboratory	ALPHATECH
Users Training	Significant training required	Minimal training required	Moderate training required	Moderate training required
Commercialization	Commercial product	Commercial product	Being commercialized	Being commercialized
Environment	Stand-alone: standard input and output to interface with other image and GIS tools	Operates within ArcGIS	Open source code Operates as stand-alone tool	Plug-in for Erdas Imagine
Approach	1. Initial processing segments image to form objects 2. Multiple classification methods (nearest neighbor, membership functions) 3. User knowledge greatly affects performance	Operates at pixel level, with conversion to vectors as the final step Currently, classification is a "black box" for the user – plans to provide more user control of processing	Genetic algorithm evolves good classifiers from primitive image processing functions, based on user-defined training sample	Initial processing based on model of the human visual system. Classifier uses fuzzy ARTMAP
Editing tools	Object-based editing within eCognition	Relies on ArcGIS editing tools	Alladin environment provides simple raster editing tools	Full suite of Erdas Imagine tools are available
3-Dimensional extraction	Have conducted research, but nothing implemented yet	Research in progress, nothing implemented yet	Currently two-dimensional extraction	Currently two-dimensional extraction

The desired end state for most NGA applications is the vector product. Conversions from raster to vector data, however, can produce anomalies that require additional editing. In the Neural Fusion

evaluation conducted at ALPHATECH, the two teams of analysts operated differently. Following the image mining step, the analyst can either clean up the raster product or convert the

raster data to vector and perform the clean up on the vector data (figure 4). Team 1 (labeled “Vector in figure 4) converted the extracted features to vectors and did the final editing on the vector data, while Team 2 (labeled “Raster”) did the cleanup on the raster product. The effect on extraction time is evident and has led NGA to investigate the general issue of raster to vector conversion.

This experience points to a fundamental challenge for developing useful tools for automated feature extraction. Although automation is the goal, it is clear that some level of manual intervention is required. As the Neural Fusion evaluation demonstrated, the stage of processing as which the manual intervention occurs can have a profound effect on the utility of the tool.

One example from this evaluation illustrates some of the difficulties in comparing manual and automated processing results (figure 5). The automated delineation of the agricultural fields shows some irregular edges, due in part to the differing spatial resolution of images fused for this task. Context and feature-sensitive post-processing could easily smooth these edges to

produce an aesthetically pleasing product. Manual processing, by comparison, yields aesthetic rectangular fields with obvious errors. The migration towards more automation suggests a need to update the standards for geospatial products.

6. Lessons Learned

These evaluations conducted by NGA have identified several promising ADE tools. Performance data indicates that a number of tools can support delineation of areal features, such as drains and landcover. Specialized tools hold promise for extraction of buildings and roads, although the performance gains are less substantial. These evaluations also point to advanced capabilities that are desirable in new ADE tools and technology. Specific requirements include:

- Smart, context-sensitive feature editing, which would streamline the clean-up process
- Automated attribution of features, to include geometric attributes and material properties
- Three dimensional extraction to locate features in X, Y and Z

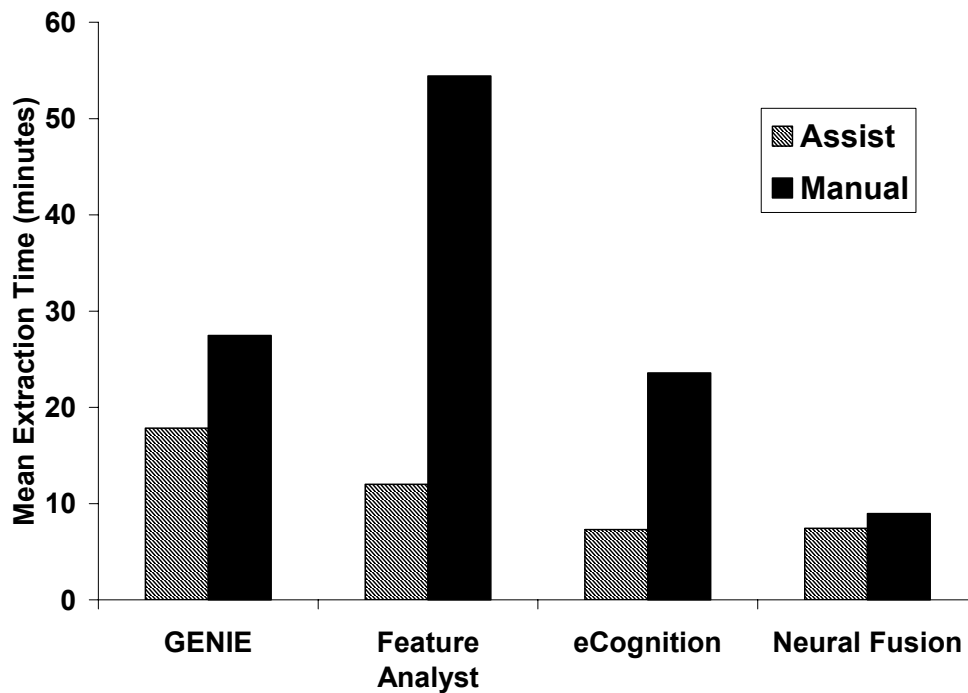


Figure 2. Mean Extraction Times for Various ADE Tools and Tests

7. Future Directions

Research and evaluations to date have shown a number of promising tools and efforts are underway to put these tools in the hands of users. Nevertheless, many challenges remain. New initiatives are exploring innovative approaches to the feature extraction problem and addressing specific issues identified in recent evaluations. The major areas for future research and development are:

- Neural ADE: Leverage recent advances in neuroscience to develop new and innovative approaches to automated and semi-automated image exploitation
- Radar ADE: Develop techniques, tools, and systems for automated and semi-automated exploitation of data acquired by radar systems to insure timely day-night, all-weather capabilities
- Automated feature attribution: Algorithms or tools that assign attributes to a delineated feature, including include geometric characteristics (length, width, height, area), material properties (asphalt road, cement road, gravel road, etc.), and “use” categories (civil airstrip vs. military airstrip)
- Smart editing: Operates in concert with ADE to provide efficient “clean up” of the ADE results. Can include context-sensitive processing, optimized user interface, and templates or geometric constraints

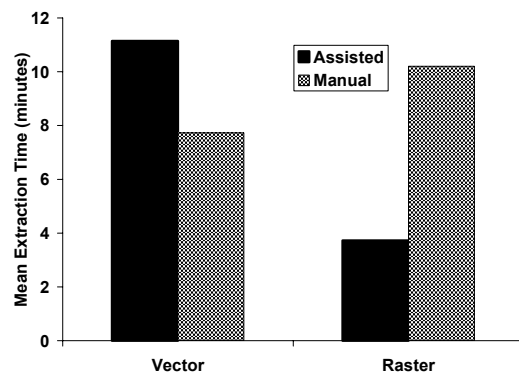


Figure 4. Extraction Times for the Neural Fusion Evaluation By Final Product

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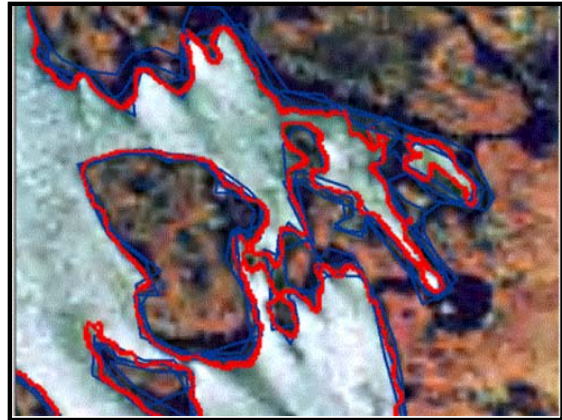
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Land Cover



Drainage



— Feature Analyst

— Manual

IKONOS - Space Imaging, Inc.

Figure 3. Comparison of Precision for Manual and Automated Extraction



Hyperion Imagery

*Provided by
ALPHATECH*

Figure 5. Extraction of Land Cover (Agricultural Areas) Using ALPHATECH's Neural Fusion Software. Images A and B show the raster level extraction performed by two different analysts. Figure C shows the vectorized result (in yellow), compared to the manual extraction manual extraction (in green).