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Environmental Security Technology Certification Program

ESTCP

Identification of Munitions Range Related Features in Topographic LIDAR Data

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Status Report
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Introduction

As part of the ESTCP Wide Area Assessment (WAA) program, multiple high-resolution topographic LIDAR data sets were collected over several formerly used munitions ranges. These data sets have been shown to contain information relating to former munitions usage at these ranges. This information typically consists of bermed or trenched features outlining target shapes, or craters resulting from the denotation of high explosives. Additional features such as roads, storage bunkers, and artillery emplacements can also be found in the LIDAR data. The locations of these features provide important information regarding historic range activities that can be used in transect design and can also be used as prior information during geostatistical analysis of related geophysical data.

Currently these range-related features are identified and recorded through manual inspection of the LIDAR data. Typically only location information is recorded. Additional information, such as size, orientation, and physical relief are not recorded because these are relatively time-consuming to document during manual inspection procedures.

Because identification and quantification of range related features provides valuable information relating former range activities that will influence the site characterization and decisions made regarding the final remediation and future use of the site, an automated, repeatable process to identify and quantify these features is desirable. An automated approach to identification of munitions related features along with supporting background documentation will be considerably more defensible throughout the site characterization process than will a manual approach to feature identification. This brief report summarizes the work to-date on efforts conducted at Sandia National Laboratories (SNL) to identify munitions-related features in topographic LIDAR data sets in an automated fashion.

To Date, efforts have focused on three main areas: 1) preparation of sample LIDAR data sets, 2) research and development of detection algorithms, and 3) development of a software platform to serve as a testing environment. Illustrations of various aspects of these main points are presented below. An example of results from this work is presented in the Current Results section of this report.

Development of Example Data Sets

To provide consistent LIDAR data for developmental and testing purposes, a series of LIDAR data sets were extracted from the various large data sets collected during WAA activities. A custom ArcGIS script was developed to extract data based on selected rectangular areas, apply a convolution filter to enhance vertical relief, and export the data for use in feature identification processing. This script allows for the rapid development of consistent sample data files from very large LIDAR data sets. The locations for the sample data sets were selected to provide a range of terrain relief and range-related feature density. Figure 1 shows a shaded relief image of an example LIDAR sample data set as extracted from the Pueblo WAA LIDAR data set.

Table 1 lists some basic characteristics of the various sample data sets developed to date.

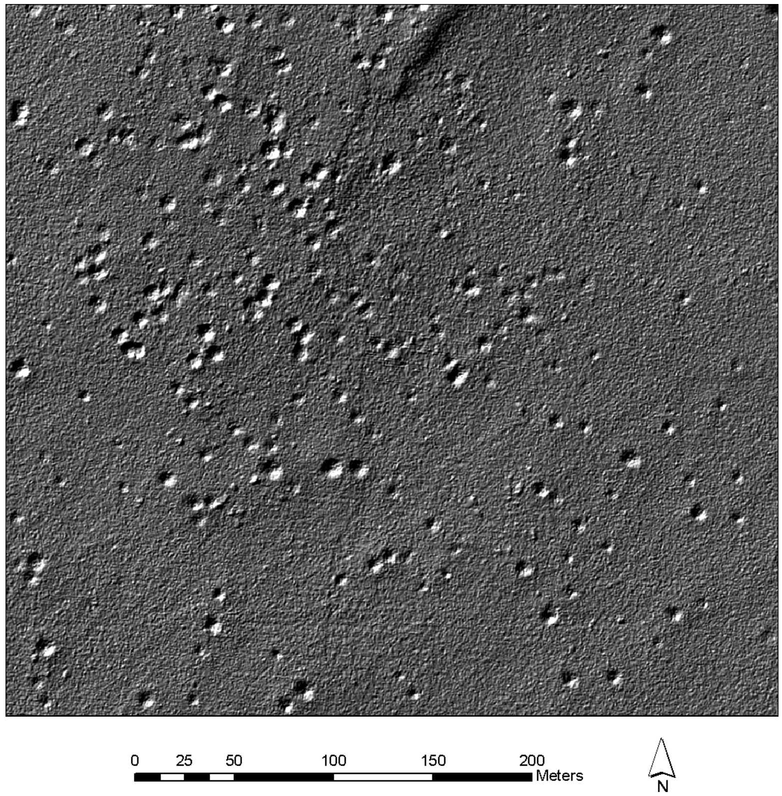


Figure 1. Shaded relief image of PA1 LIDAR data sample.

WAA Site	Subset ID	Area (hectares)	Terrain Relief	Feature Density	Feature Type
Victorville	VV1	29	Low	High	Craters
Victorville	VV2	26	Moderate	Moderate	Craters
Victorville	VV3	15	Moderate	Low	Craters
Victorville	VV4	34	High	Moderate	Craters
Victorville	VV5	44	Moderate	*None*	N/A
Victorville	VV6	670	High	Moderate	Craters
Pueblo	PA1	14	Low	High	Craters/ST
Pueblo	PA2	30	Low	Moderate	Craters/ST
Pueblo	PA3	38	Moderate	Low	Craters

Table 1. Summary information on example LIDAR data sets. Feature type of ST indicates Ship Target

Feature Identification Software

Feature identification from LIDAR data is a recent field of study. Fortunately, many of the techniques developed in image feature analysis are applicable, with modification, to LIDAR topographic data sets. To provide an environment for the testing of various feature identification algorithms, a software platform was developed in Visual Basic. This software was designed to read the sample LIDAR data files created using the custom ArcGIS script discussed above. The code is configured to allow the incorporation of various feature-detection algorithms, and is designed to allow interactive control of parameter values and provide graphical feedback. Results can be written to a GIS-compatible data file at any point in the analysis. Figure 2 shows an example of the screen display from the feature identification software. Additional details regarding this software are provided below.

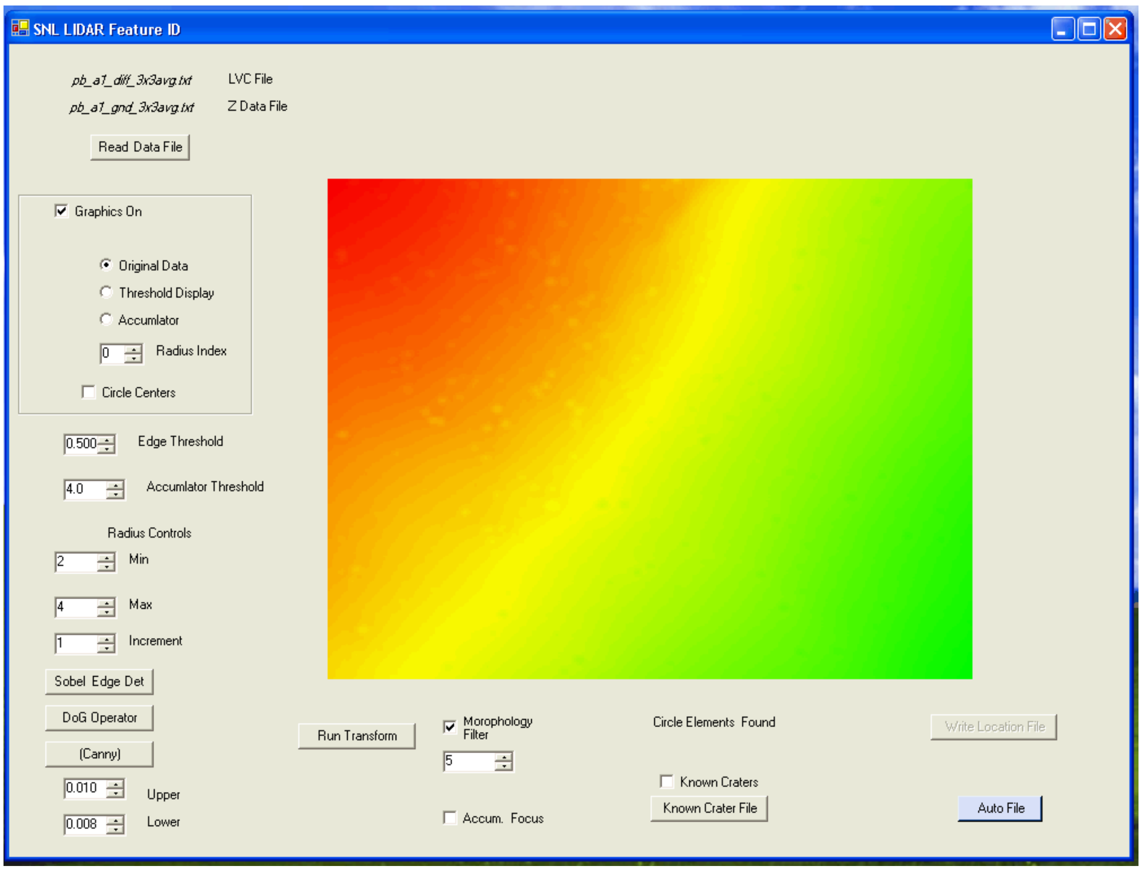


Figure 2. Screen display of SNL LIDAR Feature Identification software. Color shaded portion of image shows topographic relief from an example LIDAR data set.

Feature Identification Algorithms

Several feature identification algorithms are currently being investigated for use with topographic LIDAR data. The results presented here focus on application of the Hough Transform.

The Hough transform is widely used in image analysis for the identification of regular shapes in image data sets. This transform uses a shape-specific parameter space voting technique to identify probable feature locations. The Hough Transform has been widely researched and many variations of the original transform exist. Some modification of the original technique was necessary to allow application to topographic LIDAR data.

The first step in application of the Hough Transform is the identification of significant edges in the data set. These edges provide the basis for the recognition of regular shapes in the terrain data. Currently there are two different edge detection algorithms implemented in the SNL LIDAR Feature Identification software. These are the Sobel and Canny algorithms. Sample results from the algorithms for sample data set PA1 are shown in Figure 3 and Figure 4 respectively.

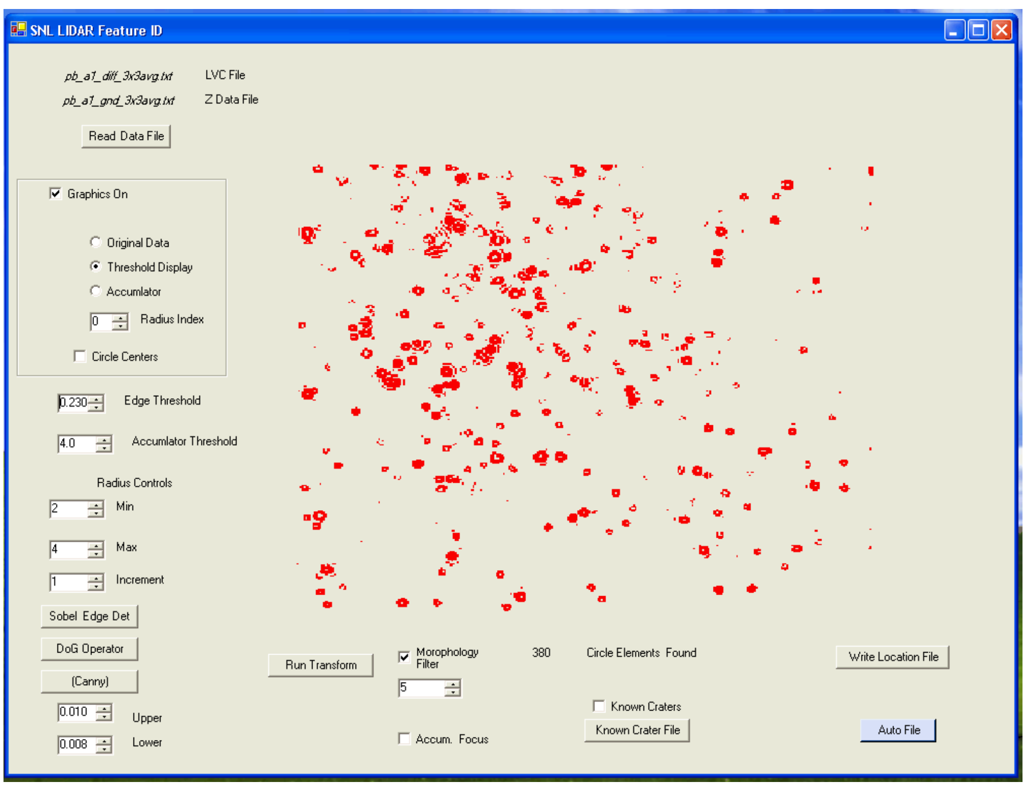


Figure 3. Example of results of Sobel edge detection within the SNL LIDAR Feature Identification software. Red points denote significant edges in the LIDAR data.

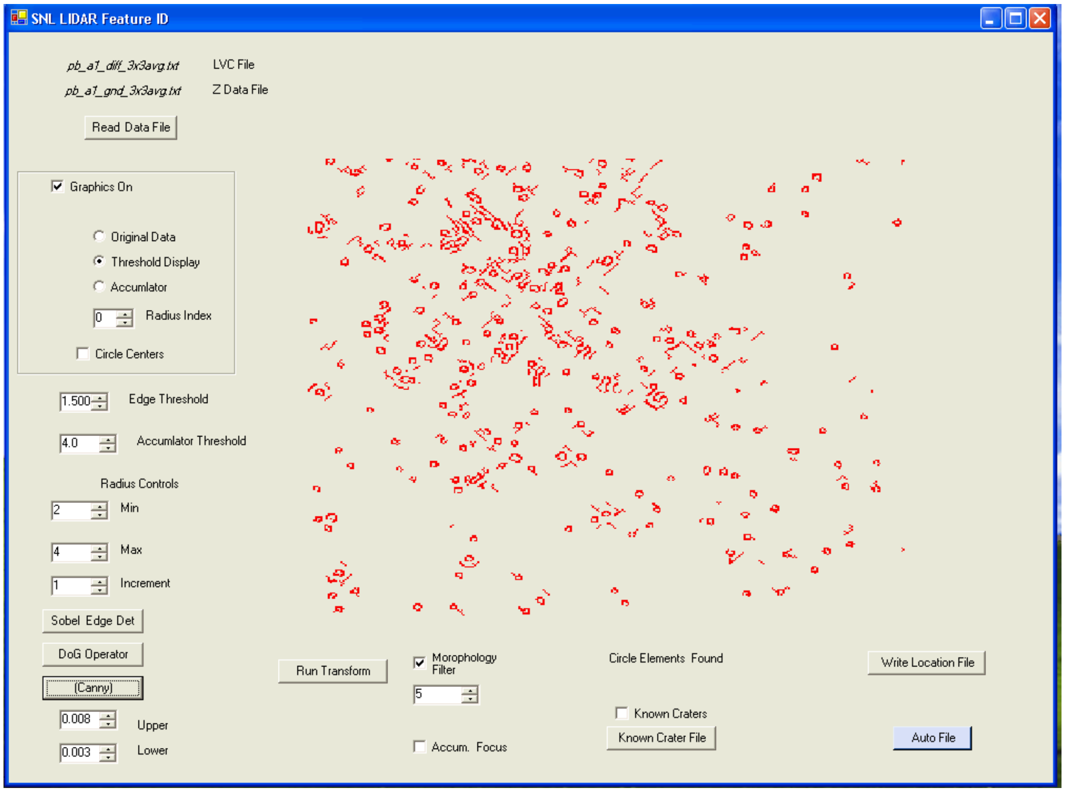


Figure 4. Example of results of Canny edge detection within the SNL LIDAR Feature Identification software. Red points denote significant edges in the LIDAR data.

Currently, feature identification using the Hough Transform is focused on the identification of probable crater features in the LIDAR terrain data. For this, the Circular Hough Transform (CHT) has been adapted for use with the digital terrain data. The CHT is highly adept at finding circular features (craters) in noisy data sets. In addition, this technique can be applied to find features of a specific radius thereby providing additional characterization of the identified feature. Figure 5 shows example results of applying the CHT within the SNL LIDAR Feature Identification software to sample data set PA1. This figure shows identified circular features (blue circles) for a single radius value; additional crater locations would be identified using different radii values. These circular features indicate probable crater locations.

Because the edge detection process is sensitive to all abrupt terrain changes, natural features such as stream channels and ridge lines will show as detected edges. These features may contain sufficient curvature to be recognized as circular features during application of the Hough Transform. To address this issue, a terrain morphology filter was developed and added to the code. This filter examines each identified feature and compares its three-dimensional shape against that expected for a crater feature. Identified features not sufficiently close to the shape of a crater are excluded from further analysis.

Figure 6 shows the results of crater identification with and without the morphology filter as calculated on sample data set PA3. The top image in Figure 6 shows feature identification results with the morphology filter turned off. As seen in this image there is a large number of circular features (blue circles) associated with a southwest-to-northeast trending drainage feature. This drainage was delineated as having strong edges (red points) during edge detection because of its steep channel sides. These channel edges have sufficient curvature so that they are misidentified as circular features during the CHT.

The lower image in Figure 6 shows feature identification results using the same parameters and data as the upper image, but with the morphology filter turned on. As shown here, the inclusion of the morphology filter removed a large percentage of the drainage related features, significantly reducing the percentage of false positive feature identifications (blue circles). Without the misidentified circular features, the strong edges of the drainage are clearly visible (red points). This clearly demonstrates the importance of this type of filter in removing non-munitions related features.

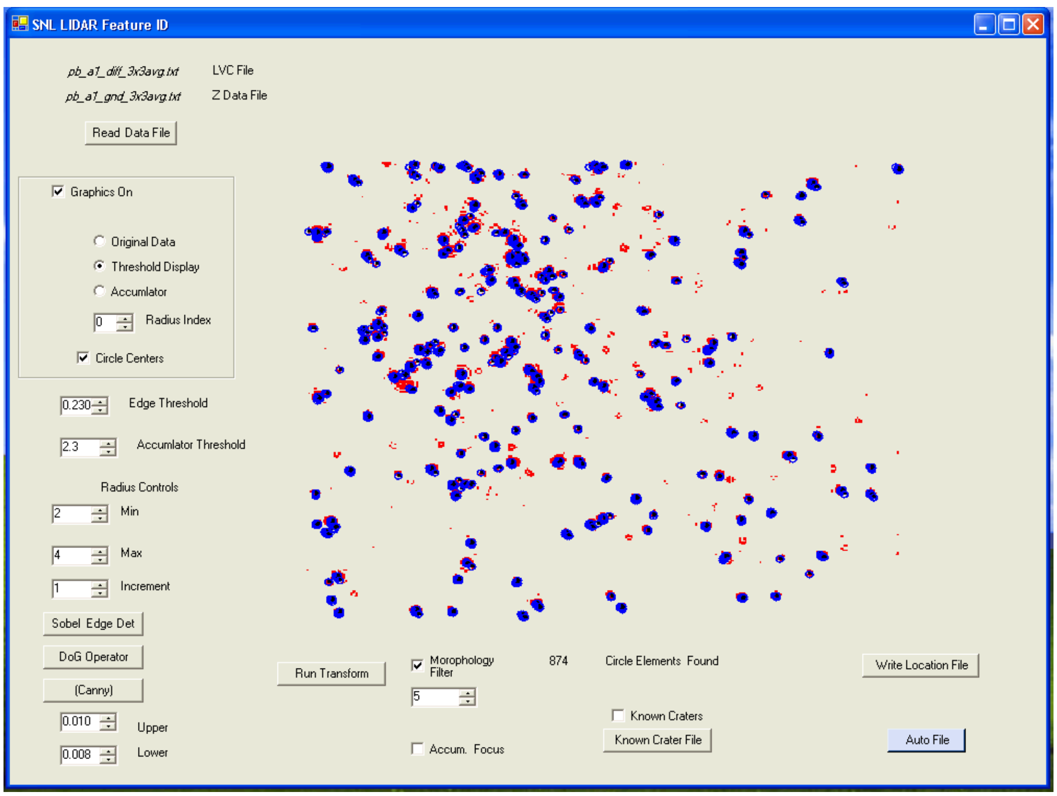
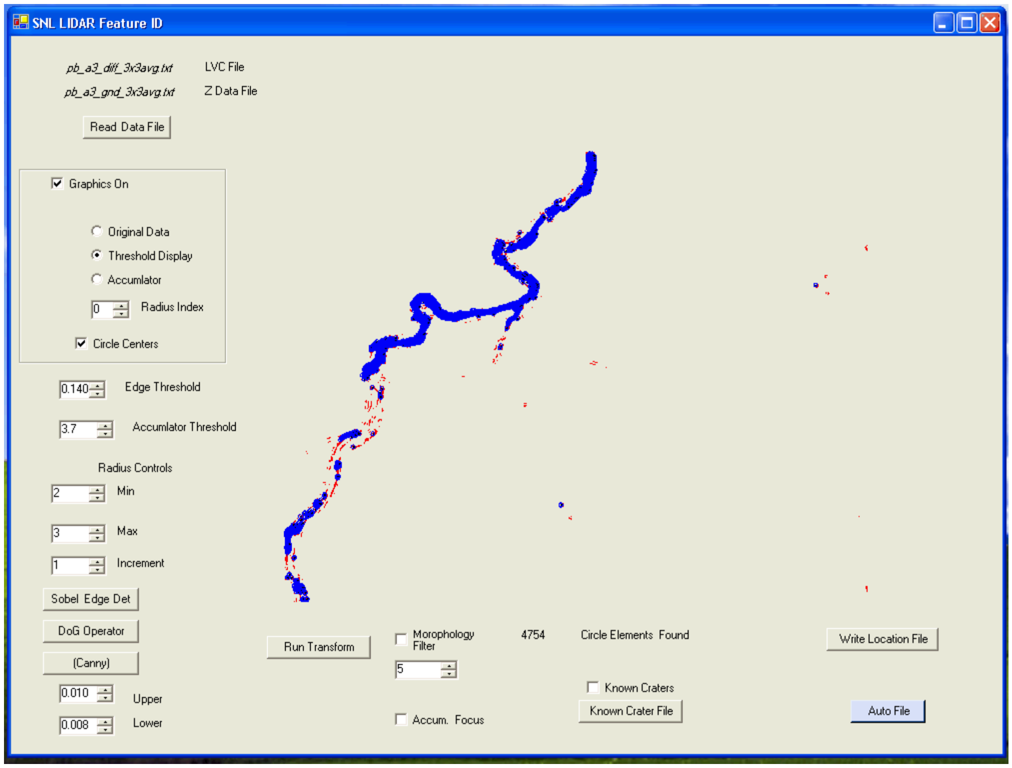


Figure 5. Results from application of the CHT to a sample LIDAR data file. Blue circles indicate identified circular features. Red points denote edges in the LIDAR data.



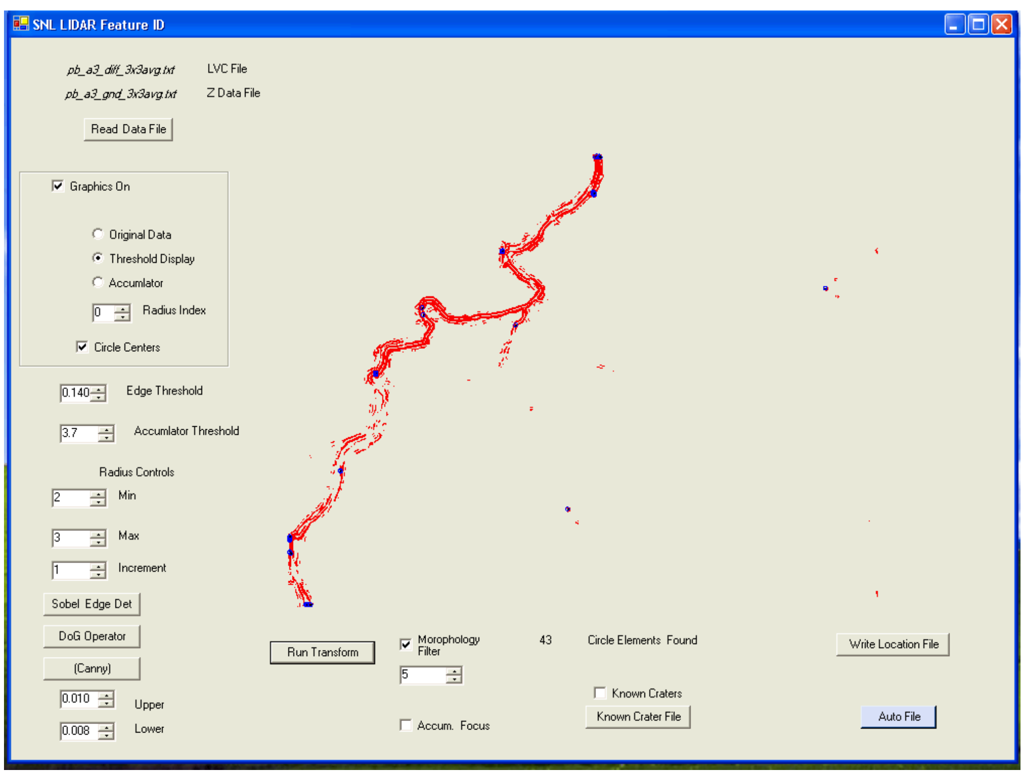


Figure 6. Crater identification results without (top figure) and with (bottom figure) use of the crater morphology filter. The major north-south running feature is a local drainage with steep channel sides. Blue circles indicate identified circular features. Red points denote edges in the LIDAR data.

Current Results

Results from the current algorithms and software code for sample data set PA1 are shown in **Error! Reference source not found.**. The upper image of this figure shows a shaded relief image of the data set; the lower portion shows the results from crater identification. Color shading in the lower image shows relative confidence in the feature identification. Red indicates high confidence, with shades of yellow and green indicating intermediate and low confidence respectively. Known crater locations identified by manual observation (see upper image) are shown with black circles. As this figure shows, the currently implemented algorithms are successful at locating a majority of the known with relatively few False Positive identifications.

Work is also underway to investigate the interaction of the various edge detection and CHT parameter settings and how they affect the True Positive Fraction (TPF) and False Positive Fraction (FPF) for various terrain types. This work takes advantage of the varied nature of the sample LIDAR data files discussed above. As the values of primary control parameters are changed, the percentages of correctly identified features (TPF) and incorrectly identified features (FPF) change. To identify appropriate parameter ranges for various terrain types, wide ranges of parameters are being applied and the resulting TPF/FPF values investigated. An example curve showing the relationship between True Positive and False Positive fractions as a function of decreasing edge detection threshold is shown in Figure 8. In this figure, the proportion of correctly identified features (TPF) is shown on the X-axis, and the proportion of misidentified features (FPF) is shown on the Y-axis. The value of the testing parameter (edge detection threshold) decreases from left to right across the plot. Misidentified features are defined as locations where the code has identified a circular feature, but no feature was identified through manual inspection.

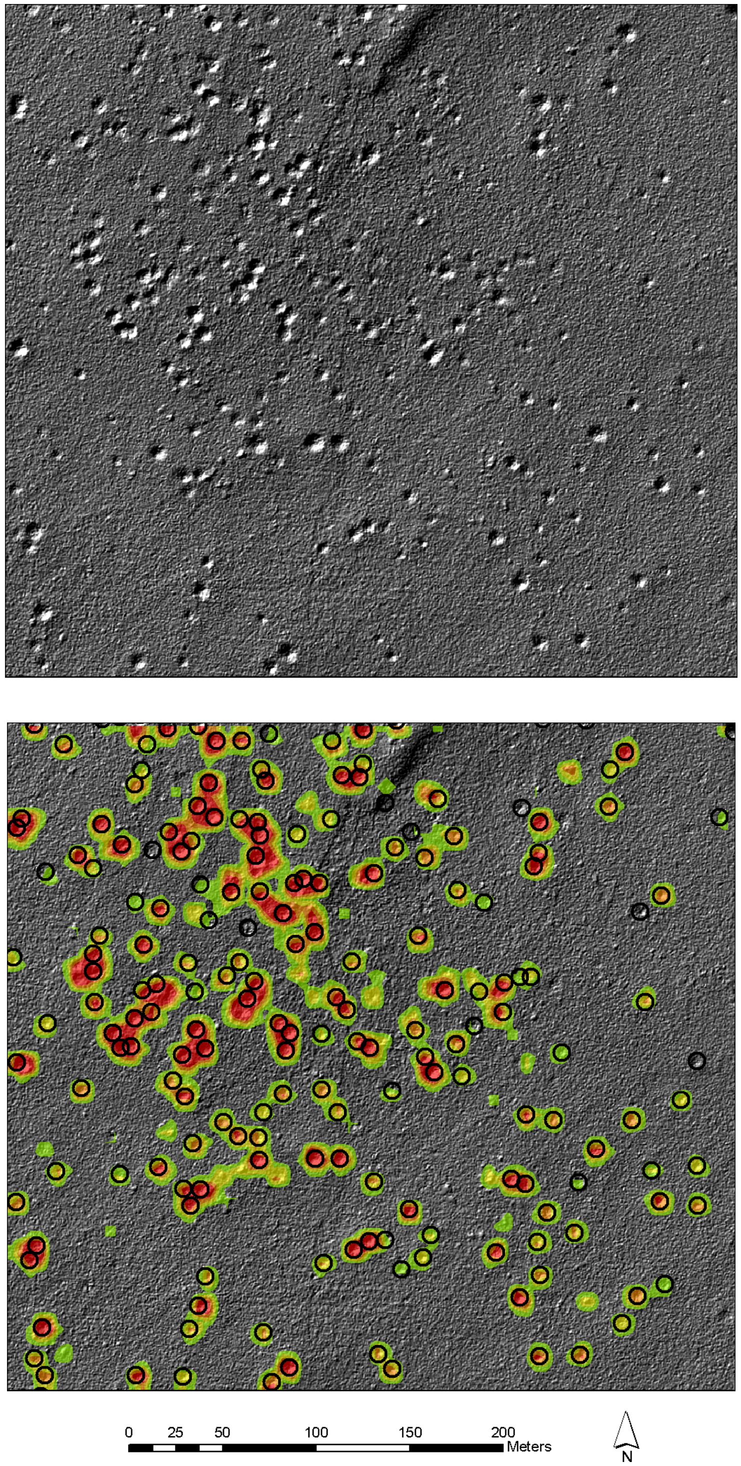


Figure 7. Topographic LIDAR data (top figure) and results from crater identification process (bottom figure) for PA1 sample LIDAR data file. In bottom figure, black circles indicate locations of manually identified crater features and color shading shows results from automated crater identification. For areas identified as containing crater features, green-to-red shading indicates increasing identification confidence.

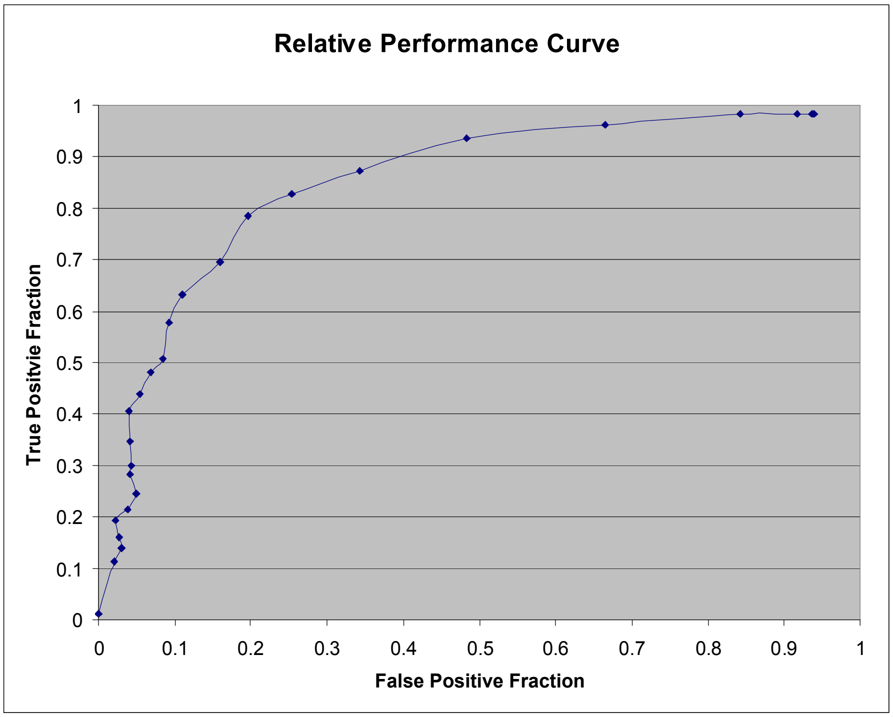


Figure 8. Graph showing relative performance of Hough transform-based crater identification algorithm as a function of decreasing edge detection threshold.

Summary of Current Status

The current version of the SNL LIDAR Feature Identification software provides primary functionality for the identification of circular features (craters) in high-density topographic LIDAR data files. This functionality is achieved through the adapted implementation of the Circular Hough Transform. Two different edge detection algorithms (Sobel and Canny) are implemented in the code to provide for the testing of these two techniques on varying data files. Two morphology filters are also implemented in the code. These filters are designed to filter-out false positive identifications generated by naturally occurring terrain features.

The interface to the feature identification code is designed to provide control of the various parameters serving as input to the feature identification process. These controls allow the investigator to alter parameter settings in an interactive manner, and an included graphical display provides immediate feed-back on the results. The graphical display allows viewing of the input data, edge detection output, and feature identification results. Additional summary statistics are also displayed in the user interface.

To provide for the quantitative evaluation of results, the feature identification code generates output files summarizing the identified features and the parameter settings used in the processing. These summary files are designed to be easily imported into the

ArcGIS software system. To allow for automated processing, the code is also designed to read in a control file. This control file contains parameter values for the various control settings and allows for executing the code for a series of control values without operator intervention. Results from each execution are written to summary output files. This process is useful when investigating large numbers of parameter settings such as during sensitivity analysis or parameter optimization.

The results from the current set of code and algorithms are encouraging. As shown in Figures 7 and 8, the current codes and algorithms perform well for crater identification with a fairly high TPF/FPF ratio. Although the TPF/FPF ratios from these initial results are promising, there are potential improvements to the algorithms which are being investigated. Further work on refining the identified locations and reducing the rate of False Positives is possible and warranted based on these encouraging results.

Continuing Efforts

Continued work for the near future is planned to focus on the general improvement of feature identification, further characterization of identified features, and the addition of additional feature types (e.g., circular target berms or ship outlines) to the recognition protocol.

General improvements in feature identification will involve aspects such as the inclusion of alternate identification algorithms, increasing the TPF/FPF ratio, identifying optimal parameter ranges, and investigating the impact of varying terrain types. These improvements will lead to a more robust feature identification process.

The inclusion of additional feature characterization information will improve our understanding of the nature of the identified features. The types of characterization information anticipated are elements such as planimetric size (length, width, diameter, etc.), orientation, vertical relief, local slope orientation, local slope angle, and nearest-neighbor distance to adjacent features. The details of this information will provide additional insight into former range usage and provide information for additional site investigations (i.e. geophysical transect planning).

The inclusion of additional feature types in the identification process will increase the applicability of the process and allow it to be adapted to different types of ranges. The identification of other features, such as arcs, straight lines, or disturbed ground can be used to identify potentially range related anthropogenic features. These features may provide useful information in deciphering historic usage and give information useful in cleanup activities.

Potential Future Tasks

Although the current research is focused on munitions-related feature identification from LIDAR elevation data, there are other aspects and potential uses of the LIDAR data which hold promise for providing value to the WAA process. Some examples of these which could be investigated in the future are listed below.

- Inclusion of LIDAR intensity values in feature identification
- Use of LIDAR data sets directly to assist in transect planning
- Use of LIDAR as a planning tool for remediation actives
    - Site access availability
    - Drainage delineation
    - Drainage planning
    - Runoff and sediment loading estimates
    - Estimating biomass volumes