AUTOMATIC MAPPING OF OFF-ROAD VEHICLE TRAILS AND PATHS AT FORT RILEY INSTALLATION, KANSAS

by

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Submitted in Partial Fulfillment of the Requirements for the
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The U.S. Army manages thousands of sites that cover millions of acres of land for various military training purposes and activities and often faces a great challenge on how to optimize the use of resources. A typical example is that the training activities often lead to off-road vehicle trails and paths and how to use the trails and paths in terms of minimizing maintenance cost becomes a problem. Being able to accurately extract and map the trails and paths is critical in advancing the U.S. Army's sustainability practices. The primary objective of this study is to develop a method geared specifically toward the military's needs of identifying and updating the off-road vehicle trails and paths for both environmental and economic purposes. The approach was developed using a well-known template matching program, called Feature Analyst, to analyze and extract the relevant trails and paths from Fort Riley's designated training areas. A 0.5 meter resolution false color infrared orthophoto with various spectral transformations/enhancements were used to extract the trails and paths. The optimal feature parameters for the highest accuracy of detecting the trails and paths were also investigated. A modified Heidke skill score was used for accuracy assessment of the outputs in comparison to the observed. The results showed the method was very promising, compared to traditional visual interpretation and hand digitizing. Moreover, suggested methods for extracting the trails and paths using remotely sensed images,

including image spatial and spectral resolution, image transformations and enhancements, and kernel size, was obtained. In addition, the complexity of the trails and paths and the discussion on how to improve their extraction in the future were given.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

BACKGROUND

The U.S. Army manages over 5,500 sites that cover roughly 30 million acres of land for various military training purposes and activities such as combat vehicle operations and field maneuvers (DEPARC 2007). These training activities can cause severe stress on the landscape. Ground cover disruption, damage to plants, potential soil erosion, habitat degradation, and landscape fragmentation are inevitable results of these training activities (Wang et al. 2009). Sustainable land carrying capacity and land conditions of the military installations are thus a great challenge the Army is facing (Jones et al. 2005).

Military's facility roads, especially the off-road vehicle trails and paths at the installations are critical for both sustainable military land carrying capacity and land condition (Ayers et al., 2005). The trails and paths provide access to the areas in which various military training programs are disposed and enhance the effectiveness of the exercises. In contrast, the trails and paths contribute to sedimentation of adjacent waterways, erosion, destruction of habitats, etc. (Gatewood, 2002; Grace, 2002). Halting the training activities will reduce the disturbance and decrease the negative impacts of the trails and paths on the environment (Egan, 1999; Elliot et al., 1999). On the other hand, the trails and paths need maintenance for sustainable military land carrying capacity, which leads to cost increase to support the mission. Closure of superfluous trails and paths can reduce the maintenance costs, limit natural expansion of roadways due to impassability, mitigate the impact of vehicular traffic to adjacent natural areas, decrease sedimentation rates, slow down landscape fragmentation, and increase quality of habitat for resident species. Throughout the Army, land managers are thus constantly faced with the challenge of optimizing limited resources in order to maintain trails and paths for safe passage of troops and equipment and reduce environmental impacts. It is very important to develop a methodology to identify and update the paths and trails for the US installations.

PROBLEM STATEMENT

The use of military off-road vehicles such as tanks in the U.S. installations inevitably fragments landscape and leads to disturbance of ground and vegetation cover and degradation of land condition. Thus, updating the trails and paths on existing road maps and determining their priorities for closure are important. As part of a research program that seeks to develop a methodological framework to assess environmental and landscape quality for U.S. Military lands to sustain both military land carrying capacity and environmental integrity, the focus of this study will be to develop a method to automatically detect and map military off-road vehicle trails and paths using high resolution satellite images and digital aerial photographs of Fort Riley, Kansas. This research will use a 2004 Fort Riley digital infrared orthophoto mosaic image at a spatial resolution of 0.5 meters and consisting of three channels: green, red, and near infrared. A template matching and machine learning approach will be developed based on existing software packages to extract trails and paths for the study area. A comparison of trail/path data obtained by automatic extraction to that derived by visual interpretation and digitizing will be conducted to calculate accuracy of the automatic extraction. Several different image transformations/enhancements will be performed such as Normalized Difference Vegetation Index (NDVI), edge enhancement, and edge detection for enhancing image interpretation. Software packages involved are ArcGIS, ERDAS Imagine, as well as their extensions that are specific for linear features extraction, including Overwatch Geospatial's Feature Analyst and GeoEye's RoadTracker. This study will result in a professional procedure that is customized for military use to update the trails and paths on the existing road maps for installations and greatly speed up the updating of road maps and advance the military land management and training planning system for the US Army installations.

RESEARCH QUESTIONS

This study will answer the following questions:

i) Can the military off-road vehicle trails and paths be identified on high resolution images and efficiently extracted via linear extraction method: template matching and machine learning approach?

ii) What spectral transformations can best enhance the interpretation of off-road vehicle trails and paths in this study area?

iii) Will the same combination of feature parameters work best for all image transformations/enhancements?

iv) Is the semi-automatic and automatic extraction of the off-road vehicle trails and paths better than the visual interpretation/hand digitization?

HYPOTHESES

The study poses these hypotheses to the previous research questions:

i) A spatial resolution of 0.5 m × 0.5 m aerial infrared orthophoto can efficiently identify and extract military off-road vehicle trails and paths via a template matching and machine learning approach.

ii) Image transformations and enhancements provide the potential to improve the interpretation of off-road vehicle trails and paths and the accuracy of extracting the trails and paths varies depending on the used algorithms and kernel sizes.

iii) The same combination of feature parameters will work best for all image transformations/enhancements.

iv) Semi-automatic and automatic algorithms for extracting the military off-road trails and paths will provide better results than visual interpretation/hand digitization.

CHAPTER 2

LITERATURE REVIEW

Since the early 1970s, there has been research into semi-automatic or automatic feature extraction from remotely sensed imagery, especially with advancements in image processing and analysis (Quackenbush 2004). There have been numerous studies that involve linear feature extraction algorithms, image transformations and enhancements, spatial resolutions, etc. The accuracy of linear feature automatic extraction often varies depending on the used images, linear feature extraction algorithms, image transformation and enhancement technologies, image spatial resolutions, and their combinations. How to combine these algorithms, technologies, and image resolutions can be a great challenge.

Different types of imagery can be used for extraction of linear feature (Quackenbush 2004), including aerial photos (Agouris et al. 2001), radar (Hellwich et al. 2002), lidar (Alharthy and Bethel 2003), SPOT (Hui et al. 2001), Landsat Thematic Mapper TM images (Wang and Zhang 2000), Ikonos imagery (Gibson 2003), and hyperspectral imagery (Gardner et al. 2001). Because of multispectral and high spatial resolutions, however, color aerial imagery is substantial for this purpose (Quackenbush 2004).

Quackenbush (2004) states that most of these studies focus on proprietary algorithms, while there are workstation and software developments. These studies especially deal with linear feature extraction techniques and their combinations with spatial and spectral resolutions and feature parameters. These combinations provide the potential for linear feature extraction, especially for automatic extraction and mapping of military off-road vehicle trails and paths. This literature review will proceed in identifying important aspects of linear feature extraction and more importantly identifying the important aspects in feature extraction of less noticeable military off-road vehicle trails and paths, which tend to be difficult when extracting due to the radiometric and geometric inconsistencies (Kaiser et al. 2004). This literature review will provide a significance of this study and the need for future research.

Various linear feature extraction techniques have been applied to extracting roads/streets on remotely sensed imagery. These include template matching technique (Hu et al. 2005, Jin and Paswaters 2006, Kaiser et al. 2004, Kim et al. 2004), fuzzy fusion techniques (Chanussot et al. 1999, Wallace et al. 2001, Yun and Uchimura 2003, Zhang and Couloigner 2006), edge finding/detection techniques (Fischler et al. 1981, Poz 2001, Ramakant and Babu 1980, Rowe and Grewe 2001), as well as other model, rule, and hierarchical based algorithms (Baumgartner et al. 1999, Couloigner and Ranchin 2000, Gibson 2003, Guindon 1998, Harvey et al. 2006, Hu and Tao 2003, Katartzis 2001, Opitz 2010, Park et al. 2005, Trinder and Yandong 1998). Several linear feature extraction professional software packages such as Feature Analyst have been developed (Blundell et al. 2008, O'Brien 2003). These techniques and packages possess their own advantages and disadvantages. Some of them can be applied to linear feature extraction of the military off-road vehicle trails and paths (Kaiser et al. 2004, Witzum and Stow 2004).

Templates are often fixed in terms of attributes such as size, shape, and intensity and features are extracted by moving the template through the image and evaluating each location's completeness and correctness to find optimal locations (Quackenbush 2004, Suetens et al. 1992). Template matching works by the user defining a template around an area of interest that quantifies a reasonable area of the entire dataset and then is matched to the entire image that has features that are under consideration (Kim et al. 2004). The algorithm applied by Kim et al. (2004) works with an image of 1m resolution. When dealing with such high resolution, the matching of not just linear features and the matching of multi-sided shapes occurs. These "roads" appear more like regions than as lines (Kim et al. 2004). Also, there are many different types of roads that need to be identified. Therefore, taking width and physical make-up affects the template matching process. (Kim et al 2004, Jin and Poswaters 2006). The specific algorithm that Kim et al. (2004) uses is based on a least square correlation matching technique. There is a process of defining an initial guess as a point along the road orientation and it is a point on a line tangential to the centerline at the template window and spacing between the target and the template window was set at a size of 25 x 25 pixels.(Kim et al 2004). This process is semi-automatic that can be much more accurate than automatic procedures, but can also take more time.

Another template matching technique developed by Jin and Paswaters (2006) is that of a semi-automated algorithm for tracking road centerlines from medium and high-resolution imagery. They implied a filtering technique that enables the continuous tracking despite failures in the matching. A road template and trajectory model was developed in conjunction with the filtering (Jin and Poswaters 2006). The algorithm behind the template matching techniques tunes the target window toward the road centerline by maximizing mutual information between the template and the target windows (Jin and Poswaters 2006). They tested this technique using a QuickBird image of 0.7m resolution and several reflectance sites were used for local testing of the template.

A more advanced statistical method of template matching was developed based on adaptive and robust Hausdorff Distance (Hu et al. 2005). Radiation distortion, geometric distortion, and random noise are all used as attitude parameters when performing the matching (Hu et al. 2005). Hausdorff Distance computes maximum distance between the template and the reference (Hu et al 2005, Huttenlocher et al 1993, Rucklidge 1997). There are several modified versions of Hausdorff distance such as the Adaptive and Robust Hausdorff Distance (ARHD) and the Adaptive Robust Reverse Hausdorff Distance (ARRHD) (Hu et al 2005). ARHD is resistant to outliers and noise, but estimates mean instead of maximum as Hausdorff Distance does (Hu et al 2005, Kwon 1996). ARRHD is more straightforward than ARHD, however it is still short of the flexibility of ARHD and even more close to the original Hausdorff Distance (Hu et al 2005). A pre-processing filtering was applied to the image and Canny Operator was used for edge detection (Hu et al 2005). There are other examples of literature that use template matching (Kaiser et al 2004, Witzum and Stow 2004), but they are of more relevance to the technologies to be mentioned later on.

Often the process of feature extraction is divided into three general steps: edge detection or road finding, road tracking, and vectorization of the detected/tracked roads (Park et al. 2002, Quackenbush 2004, Trinder and Wang 1998). Fuzzy fusion/logic techniques when producing linear features extractions can help. “Fuzzy logic in its narrow sense is all logic of approximate resonating which may be viewed as a generalization and extension of multi-value logic coextensive with the theory of fuzzy sets, that is, classes of objects in which the transition from membership to non-membership is gradual rather than abrupt” (Yun and Uchimura 2003, Zadeh 1965). Road clusters can be automatically identified using a fuzzy based classifier with specific attributes that represent the road surfaces at hand in combination with numbers of the digital pixels (Zhang and Couloigner 2006). Multi-spectral imagery was used because of the great advantage it has over panchromatic and other grey-level imagery (Zhang and Couloigner 2006). Multi-spectral imagery includes a near-infrared band which is excellent for identifying between man-made objects and surrounding features such as vegetation (Zhang and Couloigner 2006). When working with the proposed methodology of fuzzy classification and shape descriptors, a relatively high false alarm rate occurr with classifying real road pixels as non-road pixels, which in turn lead Zhang and Couloigner (2006) to use a radon transform-based linear feature detector for centerline extraction. This was an excellent choice because of its vigorous ability to withstand noise, geometric accuracy and line-width estimation. Moderate success in automating the road networking extraction from high resolution multi-spectral imagery was concluded (Zhang and Couloigner 2006).

Chanussot et al. (1999) proposed two strategies of fusing images together of the same geometric properties, but different temporal aspects. A detection algorithm was used on the fused imagery for linear feature extraction. They used a pre-filtering operator to smooth noise and preserve the structures followed by a directional filter for linear uniformity (Chanussot et al 1999). Results from all of the fusion techniques led to various results, with none of them standing out from the rest. However, false alarms in the mountainous regions were present throughout the final images (Chanussot et al 1999). Wallace et al. (2001) worked with standard military geospatial products such as Digital Terrain Elevation Data (DTED) and Vector Map data (VMap). Datasets that were employed included multi-spectral, panchromatic, and radar imagery. Multiple algorithms to maximize reliable linear feature extractions from target images were used and the process of automatically identifying as many as possible within a specific spatial context was done for contextual information (Wallace et al. 2001). A fuzzy logic and Bayesian probability were being tested that allows for flexible parameters to model most joint probability distributions (Wallace et al. 2001). Training is done using a sample of 1500+ linear features that have been extracted and attributed with different values provided to represent the different properties of the study (Wallace et al. 2001). Datasets of medium and high resolution were used in the study. Global passes of extraction were made through the medium resolution imagery and then reapplied to the high resolution imagery.

A particular useful fuzzy logic study was presented by Yun and Uchimura (2003) for road extraction in rural areas from high resolution imagery. Two factors were investigated in this study: high resolution and user-guided extraction. A road model, based on gray level pixels and road width/direction, was accompanied by histogram value identification of each band and then fuzzy filtering of each band (Yun and Uchimura 2003). A Deriche edge operator was used for edge detection (Lanser and Eckstein 1992, Yun and Uchimura 2003). The results from the studies showed the great potential of fuzzy reasoning.

Other methods of semi-automatic and automatic feature extraction were much more difficult to group into categories, but still provide useful information on feature extraction techniques as well as different spatial, spectral, and feature parameters used in conjunction with those techniques to offer potential procedures for this study. For example, hierarchical procedures were provided as methods for linear feature extraction by Couloigner and Ranchin (2000), Gibson (2003), Hu and Tao (2003), and Opitz (2010). Couloigner and Ranchin (2000) presented a new method to hierarchically extract urban road networks from very high spatial resolution via multi-resolution analysis and Wavelet Transform. They worked with Gaussian kernels for multi-resolution analysis (Couloigner and Ranchin 2000, Mayer and Steger 1996) as well as fusing 2m and 0.25m resolution images. Modeling roads using the multi-resolution and wavelet transform analysis is an efficient method for multi-scale representation and allows for precise extraction of edges (Couloigner and Ranchin 2000).

Gibson (2003) used a different hierarchical approach for extraction of roads. The algorithm worked as a road detector under grayscale thresholds, edge maps or in multispectral data, however, each detector alone failed under some set of conditions (Gibson 2003). Edges were detected via a modified Nevatia-Babu edge detector and a Tasseled Cap Transform (Kauth and Thomas 1967, Crist and Cicone 1984) was also used as a fixed feature space transformation for agriculture and vegetation (Gibson 2003).

Hierarchical grouping can be used for fragmenting line segments (Hu and Tao 2003). This was done using image resolutions of 1m and 2.8m from IKONS and Quickbird images (Hu and Tao 2003). A Guassian mask filtering was used to smooth the images, while afterwards horizontal and vertical directions were used for computing the correlation coefficient between the binary template and the images (Hu and Tao 2003). A hierarchical approach can also be applied for removing classification errors through a “data-driven” process. This was done in Feature Analyst® (Opitz 2010) and will be discussed in a later section. Other algorithms and their combinations include Watershed transform and shock graph algorithm to obtain centerlines (Park et al 2005), classification approaches of unsupervised and supervised classifications such as K-means, Fuzzy C means, ISODATA, Maximum Likelihood, Minimum Distance, Mahalanobis Distance, and Spectral Angle Mapper Classification (Repaka and Truax 2004).

Reviewing all of this literature has led to some justified methods in comparison to specific literature and the proposed study. There has been very little research done on extracting trails and paths from remotely sensed imagery (Kaiser et al 2004, Wiztum and Stow 2004). Kaiser et al. (2004) is proposing a study area in Southern California, of gently rolling terrain covered by sparse to moderate density chaparral shrub vegetation, for extracting smuggler trail networks crossing the US-Mexico border. This proved to have some degree of difficulty because the trails have less geometric and radiometric consistency than roads and the method tend to be very sensitive to pattern disturbances such as traffic markings, vehicles, or shadows (Kaiser et al. 2004, Witztum and Stow 2004).

For extraction of trails, Kaiser et al. (2004) proposed a three-step approach: i) Various image processing was first applied to the imagery; ii) Trail length comparison between the imagery processed before and the GPS derived lengths was conducted;

and iii) Finally, a neural network technique was used to extract trails and then compared to GPS derived lengths. ERDAS® Imagine was used for the image enhancements/transformations. The used images had a spatial resolution of 0.6m and consisted of four bands: Visible blue, green, and red, and near-infrared. The image enhancements included: normalized difference vegetation index (NDVI), spectral mixture analysis (SMA), the third principal component (PC3) from principal components analysis (PCA), and a color composite image of PC1 (the red band), PC2 (the green band), and PC3 (the blue band). NDVI produced a substantial increase in suspected trails mapped, PC3 produced more obvious trails and less suspected trails, and the color composite produced a slightly more obvious amount of trails, but less suspected than PC3. (Kaiser et al. 2004). Kaiser et al. (2004) then took the approach of having at least two separate analysts using conventional, interactive image interpretation and digitizing methods evaluate the enhancement/transformation approaches.

The final step was applying a neural network feature extraction via Feature Analyst®. Feature Analyst® is a software extension to several GIS and image processing programs such as ArcGIS and ERDAS Imagine. The extension employs machine-learning techniques to address a range of image analysis procedures (O'Brien 2003). The user gives the system a sample of extracted features from the image, the system automatically develops a model that correlates the known data, and a learned model classifies and extracts the reaming target objects in the image (Bludnell et al. 2008, O'Brien 2003). In conjunction with Feature Analyst, RoadTracker is a proprietary application for for collecting road centerlines created by Feature Analyst from multi-spectral imagery (Blundell et al. 2008). Roadtracker is an extension to Feature Analyst®

that can be used not only to collect paved and unpaved roads, but also to extract other linear features such as trails and paths (Blundell et al. 2008). A combination of these two extensions can reduce extraction time by a factor of five to ten over small areas (O'Brien 2003). In combination with the extraction algorithms, both extensions have other tools such as cutting-edge statistical and machine-learning algorithms to model the feature-recognition process, tools to remove clutter, and ability to encompass elevation datasets (Blundell et al. 2008, O'Brien 2003). Kaiser et al. (2004) concluded that a combination of spectral mixed analysis (SMA), Feature Analyst®, followed by manual interpretation, delineation, and editing produced the highest overall accuracy results.

Feature extraction is becoming more and more important, especially in the interest of road network extraction for GIS databases (Quackenbush 2004). Quackenbush (2004) reviewed several articles that were related to feature extraction, like what was done in this literature review. He stated that companies such as Definiens and Visual Learning Systems were developing software specifically targeted at linear feature extraction. Reviewing these articles led me to discover these targeted feature extraction programs and find one that was of particular interest and that had been used in a study that was similar to the problem statement (Blundell et al. 2008, Kaiser et al. 2004, O'Brien 2003). Using the parameters in these studies, as well in combination with other studies reviewed, there should be a case for developing sound methodology for extracting military off-road vehicle trails and paths from remotely sensed imagery for this study.

CHAPTER 3

MATERIALS AND METHODS

STUDY AREA

The area of interest for this study is located at Fort Riley, Kansas (Figure 1), a military base that has been in operation since 1853, located near Manhattan, Kansas (Pride 1997). The land coverage of Fort Riley consists of 41,154 hectares (approximately 101,693 acres) and is located in the blue Stem Prairie section of the Tall Grass Prairie biotic province (Bailey 1976). Average monthly temperatures range from below -2°C in the winter to above 26°C in the summer, while precipitation reports show that the average annual rainfall is 83.5cm (Althoff et al 2005, Hayden 1998). There are three major land cover types throughout the installation (Figure 1): grasslands, shrublands, and woodlands (Althoff et al 2005). In addition, some built areas can be found in the south part of this study area. The majority of the soil at Fort Riley is classified as a Wymore-Irwin association of deep, nearly level to sloping silt loams (USDA Soil Conservation Service) that tend to be drought prone and are subject to water erosion when vegetation is removed or disturbed (Althoff et al 2005).

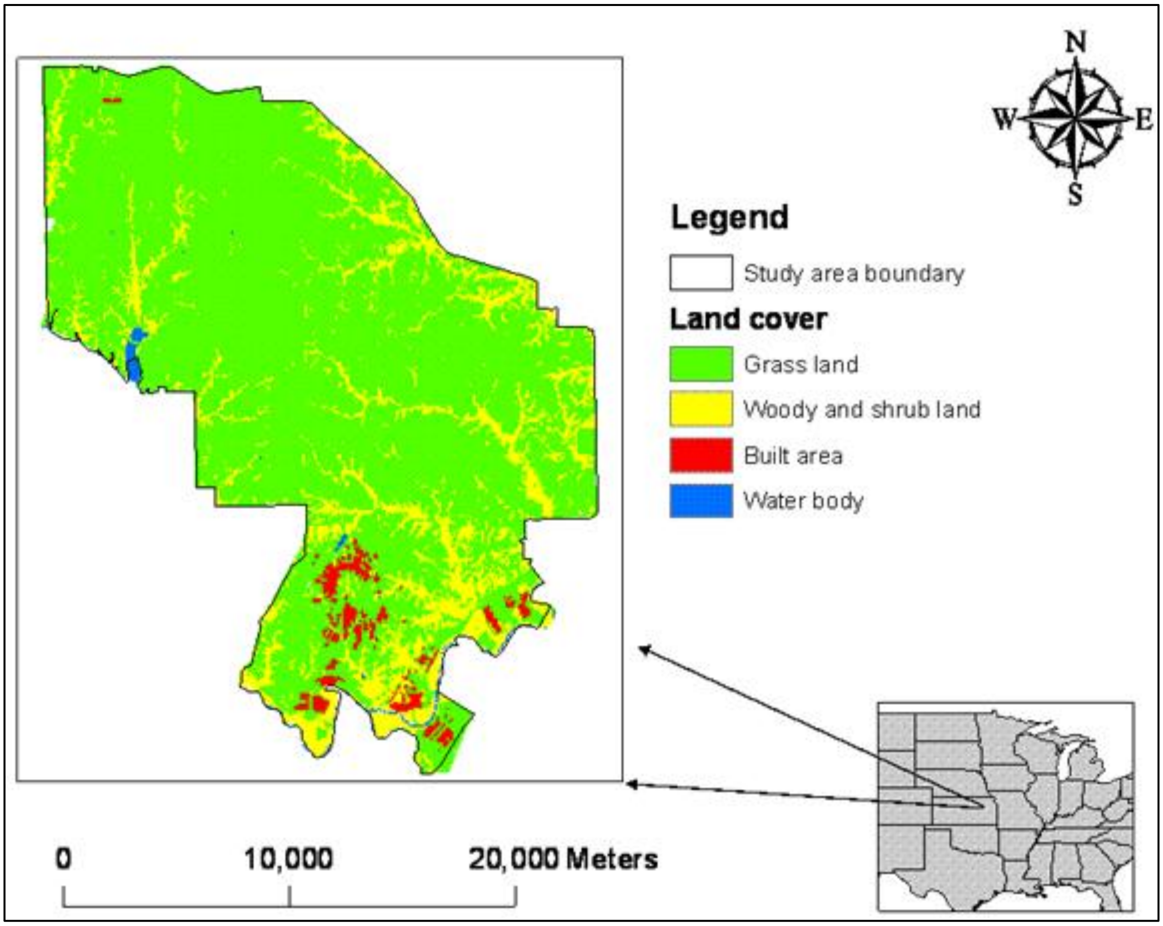

Figure 1. Study area and land use/cover categories.

DATA SETS

The datasets of interest for this project includes a digital infrared orthophoto mosaic image of Fort Riley (Figure 2). This image was acquired in 2004 and used for mapping the trails and paths. It is a multi-spectral image that consists of three bands: green, red, and near infrared. The spatial resolution is 0.5 meters. An enlarged area is shown in Figure depicting some military off-road trails and paths are demonstrated. On the false color infrared, the trails and paths had light tones and could be easily discerned. The near-infrared channel allows for contrast between the bare soil and the vegetation. With a standard set of channels, there would not be a noticeable difference between the bare soil and the vegetation. However, the near-infrared channel turns the vegetation to a red color and the bare soil begins to reflect a white color that allows for a better visual interpretation between the bare soil and the vegetation.

The other dataset of interest is an already visually interpreted, digitized trail and path map that was overlaid on an aerial photo (Figure 4) (Johnson et al 2010) and this was used for accuracy comparison. In addition to the existing roads, new trails and paths were visually identified and digitized on the high-resolution color infrared photograph. All the roads within Fort Riley were classified into five classes (Johnson et al. 2010): 1) primary roads - hard surfaces (e.g., freeway, state highway) for all weather, 2) secondary roads - hard surfaces for all weather but lower quality than the primary roads, 3) light duty roads - hard or improved surfaces (e.g., residential street, rural road, or graveled road), 4) trails - the improved roads with no maintenance and unimproved dirt roads, and 5) paths - tire tracks. The trails could be interpreted on the image because they were easily discernible with no or very sparse surrounding vegetation. The paths had some tire tracks present, but were typically better seen from above than on the ground.

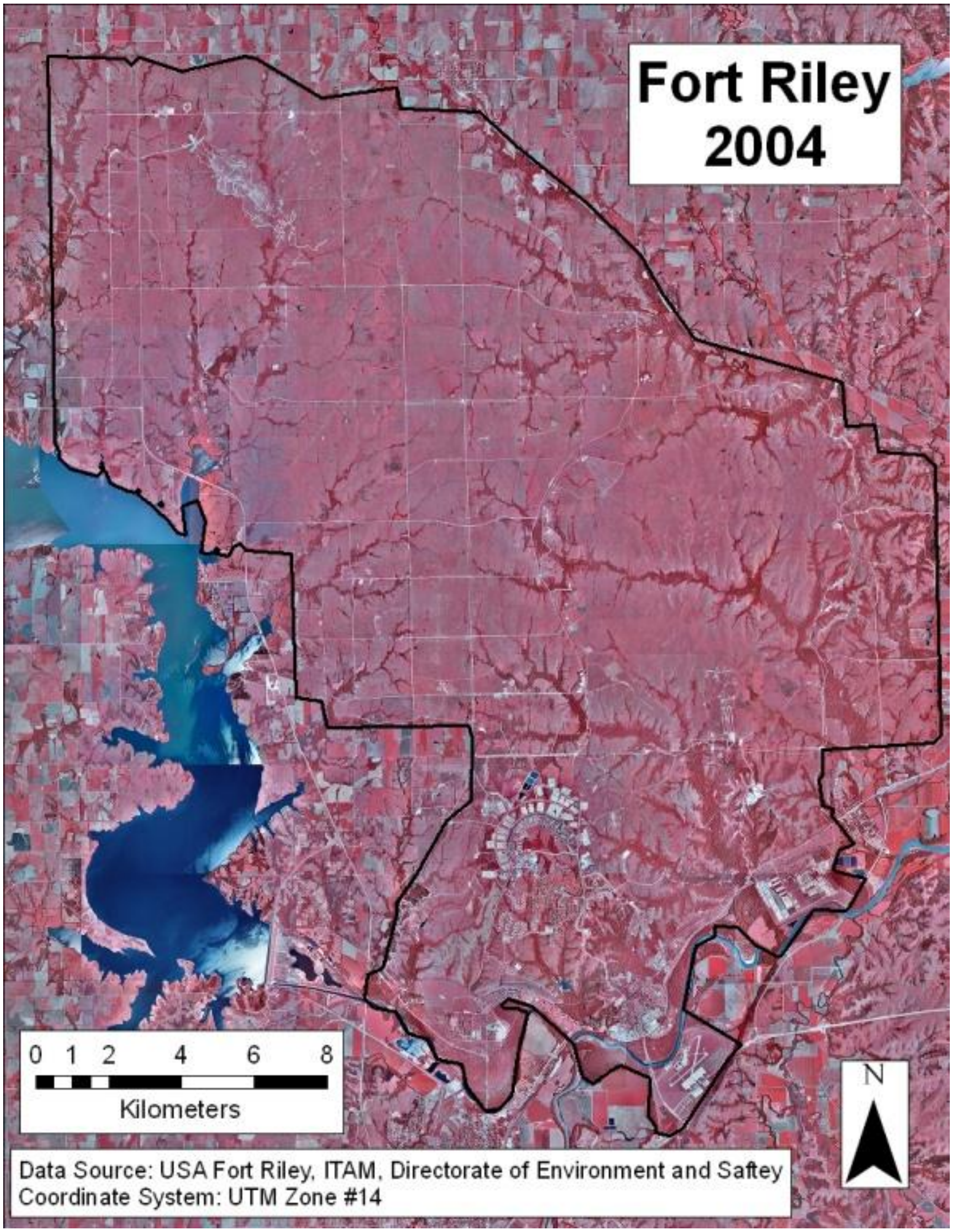

Figure 2. Digital color infrared orthophoto mosaic image of Fort Riley.

Figure 3. An enlarged area to show military off-road vehicle trails and paths.

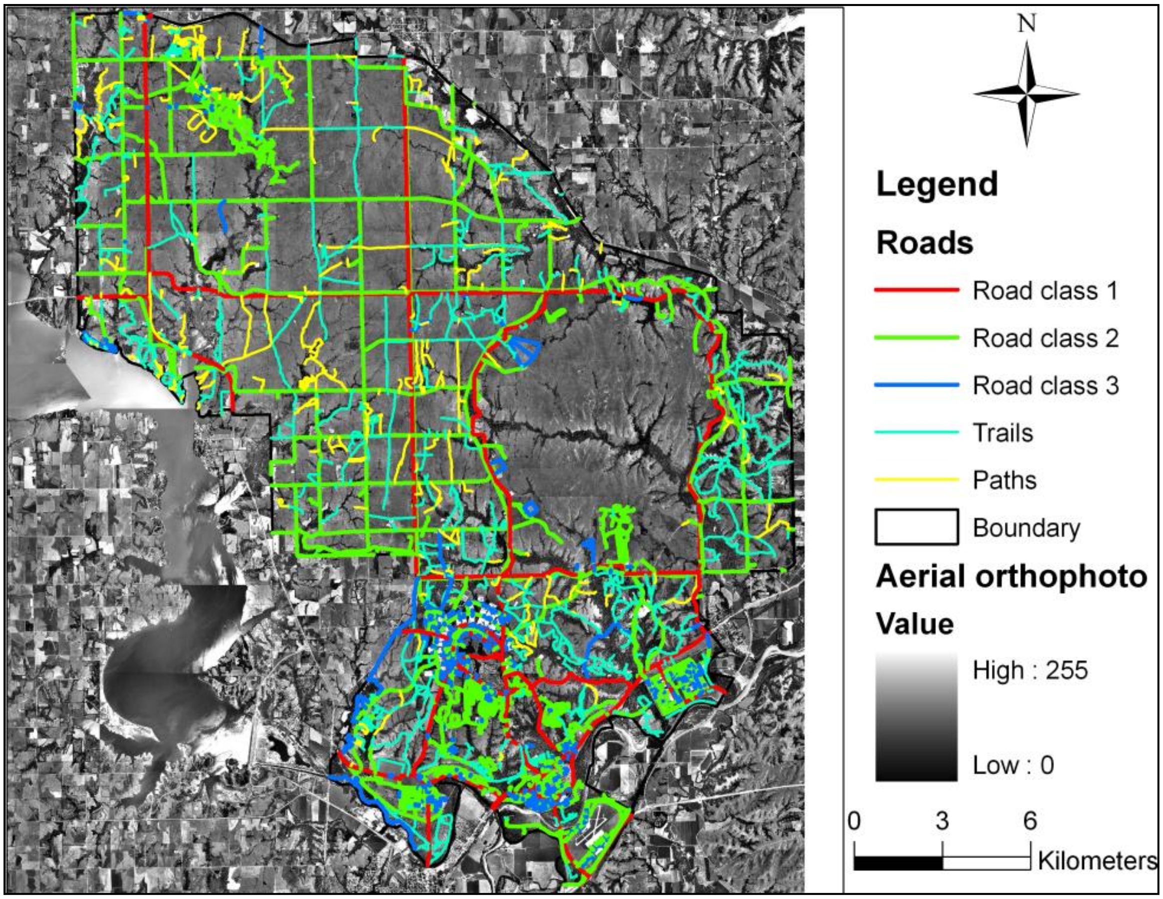

Figure 4. The path and trail map of Fort Riley obtained by visual interpretation overlaid on a digital color infrared orthophoto by Johnson et al. (2010).

<u>MEHTODS</u>

With emphasis on environmental quality, this research aimed to develop a methodology for automatically identifying and mapping military off-road vehicle trails and paths using a high resolution color orthophoto by creating and collecting vectorized data of the trails and paths efficiently and accurately. The extraction of the trails and paths consists of a four step process: pre-processing, roadway finding (edge detection), roadway tracking, and vectorization (Park et al. 2005). Geometric correction and radiometric correction of the image and analysis of results were also conducted to round out the optimal methods for the linear feature extraction.

Figure 5 shows the proposed steps for extracting the linear features for Fort Riley Installation. A color infrared digital aerial orthophoto has been collected and used to test various techniques and procedures for extracting these linear features. The reason to use this false color infrared image include: i) this image consists of green, red, and near infrared bands and shows great difference of spectral reflectance between the vegetated areas and bare soils and ii) disturbance will reduce canopy cover and thus greatly decrease the reflectance in near infrared, which will make the trails and paths interpretable. The process for extracting information from remotely sensed data tells of the necessity for digital imagery preprocessing such as geometric and radiometric correction (Jensen 2005). In this study, however, this used image is a color infrared orthophoto that means geometric and radiometric corrections have been completed. Moreover, the used orthophoto has had a desirable coordinate system. Thus, geometric and radiometric corrections for this image are unnecessary.

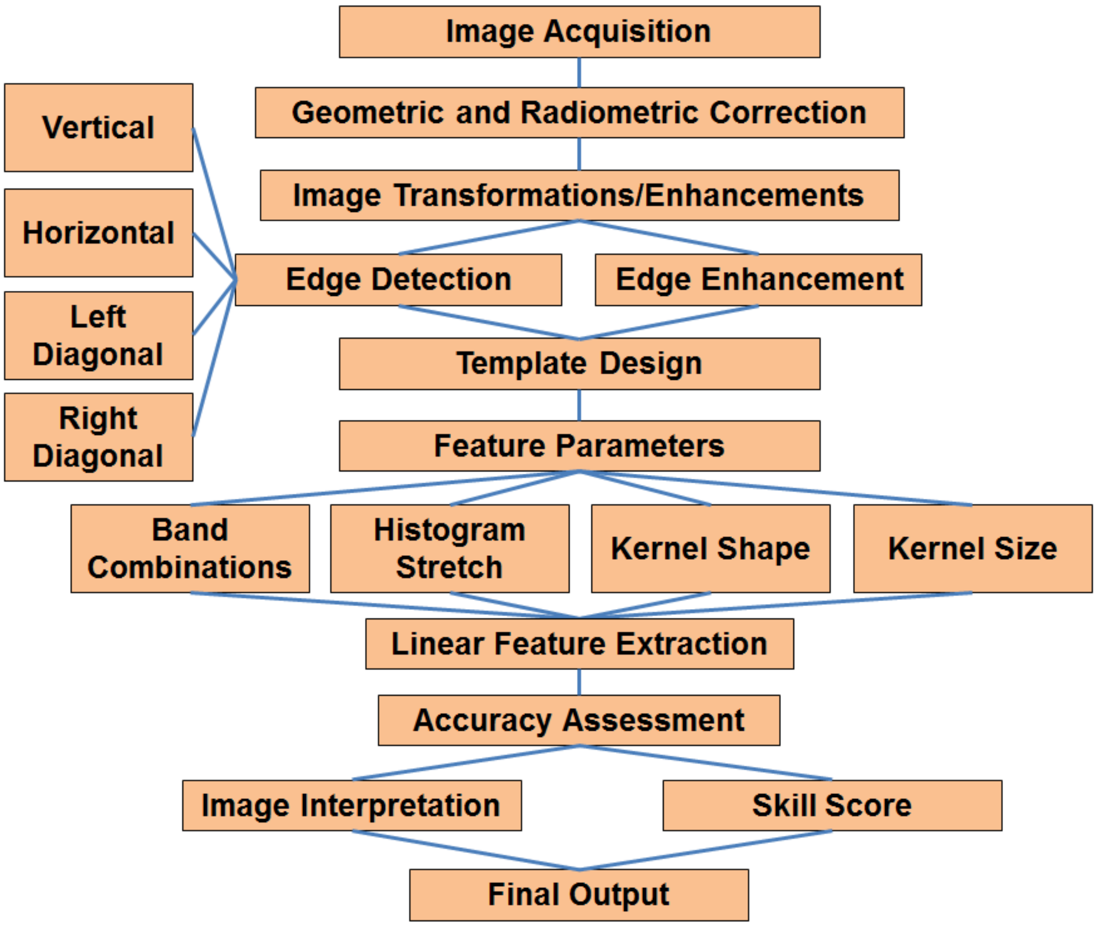

Figure 5. Methodological framework for extraction of military off-road vehicle trails and paths.

Image transformations and enhancements, spatial adjustments, and feature parameters all contribute to increase of accuracy for automatic extraction of the linear features – trails and paths (Kaiser et al 2004, Witzum and Stow 2004). Image enhancements and transformations often provide the potential to improve identification and extraction of linear features (Kaiser et al 2004, Witzum and Stow 2004). There are various image enhancement and transformation methods available, including normalized difference vegetation index (NDVI), spectral mixture analysis (SMA), edge enhancement, and principal component analysis. Edge enhancement is a popular method for extraction of roads and the other three have also proved useful for detecting these paths and trails (Kaiser et al 2004, Witzum and Stow 2004). ERDAS Imagine® 9.3 was used to perform and compare the image enhancements.

In order to extract the trails and paths for Fort Riley, the image enhancement and transformation methods to be used in this study focus on edge enhancement, edge detection, vertical edge detection, horizontal edge detection, left diagonal edge detection, and right edge detection (Figure 5). The edge enhancement methods help delineate edges and make the linear features more interpretable than in the original image (Jensen 2005). To cut down on processing time and have more accurate extractions, three samples plots, 2000 meters by 2000 meters in size, were selected for this study.

Edge detection is a digital image process that applies more emphasis on drawing out the edges of features, but the image is greatly degraded overall. The variations of edge detection put more emphasis on the directions of the edges in the image. Therefore it was found necessary to attempt the major directions of the kernels for edge detection. Both are confident choices for image enhancements and allow for different viewpoints of feature extraction. Preliminary tests were conducted on what the best kernel size would be for performing the enhancements and/or transformations in combination with visual interpretation of image degradation of too large of a seven by seven kernel and the lack of upgraded quality of the three by three kernels. Still all three kernel sizes will be applied in testing.

Figure 6 shows the image transformations/enhancements kernels that were applied to the color infrared image. These filters were applied to each pixel in the image with the center of the filter focused on each pixel individually. The pixels that are within range of the center focus pixel are also affected by the filter. This allows for an even distribution of the filter on the entire image. Edge enhancement filters focus on less distortion of the image while defining th edges that have a higher contrast between the surroundings. This amplifies the edge from the rest of the image, however it works best for edge that are well defined to begin with.

-1	-1	-1	-1	-1
-1	-1	-1	-1	-1
-1	-1	49	-1	-1
-1	-1	-1	-1	-1
-1	-1	-1	-1	-1

Edge Enhancement

-1	-1	-1	-1	-1
-1	-2	-2	-2	-1
-1	-2	32	-2	-1
-1	-2	-2	-2	-1
-1	-1	-1	-1	-1

Edge Detection

-1	-1	0	1	1
-1	-1	0	1	1
-2	-2	0	2	2
-1	-1	0	1	1
-1	-1	0	1	1

Vertical Edge Detection

-1	-1	-2	-1	-1
-1	-1	-2	-1	-1
0	0	0	0	0
1	1	2	1	1
1	1	2	1	1

Horizontal Edge Detection

0	1	1	1	2
-1	0	1	2	1
-1	-1	0	1	1
-1	-2	-1	0	1
-2	-1	-1	-1	0

Left Diagonal Edge Detection

-2	-1	-1	-1	0
-1	-2	-1	0	1
-1	-1	0	1	1
-1	0	1	2	1
0	1	1	1	2

Right Diagonal Edge Detection

Figure 6. Image enhancement/transformation kernels.

Spatial resolution has proven crucial to the different algorithms that have been implemented to different study areas in many of studies of linear feature extraction

(Baumgartner et al. 1999, Fischler et al. 1981, Guindon 1998, Hu and Tao 2003, Kaiser et al. 2004, Kim et al. 2004, Repaka and Truax 2004, Witzum and Stow 2004, Zhang 2006). Spatial resolutions of the existing images that were used for extraction of linear features vary from 0.5 m to 30m. Often multi-spectral and high spatial resolution images have more potential to be used for automatic extraction of linear features (Quackenbush 2004). The research being conducted at Fort Riley was using a multi-spectral high resolution image. Working with the military off-road vehicle trails and paths, the multi-spectral and high resolution image allows for an easier detection between the trail/path itself and the immediate land cover bordering it, mostly consisting of grassland and small shrubbery that have high brightness values that can sometimes be difficult to distinguish the trails and paths from.

In addition to image transformations and enhancements and spatial resolutions, the heart of the feature extraction revolves around the procedure itself. In this study, a template matching/machine learning approach was used via Feature Analyst®. This is an adaptive-learning software program that utilizes a neural network extraction model to identify and detect features having both spectral and spatial characteristics that resemble the user's target template (Blundell et al. 2008, Kaiser et al 2004, O'Brien 2003, Opitz 2010, and Yun 2003). Feature Analyst® has several different menus and tools that the user can access to, such as removing clutter, raster to vector, combining features, erode/dilate image, aggregate features, and convert to line. Optimal local sites are chosen to produce the highest accuracy template for feature extraction. To accomplish the selection of sites, a temporary grid is placed over the image data for identification of sites that have linear features that could be used for the creation of the template for machine learning. In this study, these grids are 2000 by 2000 meters and there are a total of 210 to examine (Appendix A).

When working with Feature Analyst® trails and paths that are desired for extraction are selected by the user in a semi-automatic feature extraction fashion. The feature analyst system then automatically develops a model that correlates known data (Blundell et al. 2008). This model is then applied throughout the entire image. The set created can be fine-tuned through additional training examples that create an even more precise model for extraction. After training the model for identifying the features the first time, it becomes necessary to train the model a second time for removing linear features that are not the trails and paths pertinent to the study. This could be a time consuming process due to user's misclassification and lack of knowledge of the program and image interpretation, etc. Working with the initial feature extraction has the possibility of being the toughest part of the project based on skill and duration.

With Feature Analyst being a general feature extraction that can extract anything from vegetation and drainage features (O'Brien 2003) to buildings and roads (Blundell et al. 2008), there can always be time improvement in the form of a more specialized feature extraction program. There is an additional add-on used for the trail and path extraction, RoadTracker 2.0. RoadTracker is a proprietary application that was built for collecting road centerlines of the highest quality from different remotely sensed imagery (Blundell et al. 2008).This extension helps to speed up linear feature detection from panchromatic and multi-spectral imagery (Feature Analyst 2010).

The feature parameters associated with Feature Analyst are important in executing the optimal extraction of the trails and paths. Important parameters for

Feature Analyst were explored such as the linear feature width being less than or greater than 10 meters wide. Feature Analyst also allows for the selection of input bands. This allows for what bands to be selected and what combinations/order they are in. Another parameter associated is the histogram stretch. The optimal histogram stretch can help delineate the trails and paths better in certain histograms versus that of others, therefore finding the best fit histogram is an important parameter for feature extraction. Options for histogram stretch include standard deviation and histogram equalization. In addition, the important parameters also include the kernel shape and size, referred to as input representation in Feature Analyst, for distinguishing one feature from another. This allows for input shapes such as square, circle, manhattan, and bull’s eye. The size of these input kernels can be changed in correspondence of image pixel size and the shape/width of the features to be extracted. These selections can lead to different combinations of the used parameters and thus different maps of extracted trails and paths.

Statistical analysis and accuracy assessment is important to developing an ontologically sound methodology to back up the model produced from the linear feature extraction. For statistical purposes, previously hand digitized trails and paths from the same photo were used for comparison to the automatically extracted features. Before implementing any statistical analysis, there has to be some visual interpretation of the extracted features from the enhanced/ transformed images as well as a comparison between them and the original hand digitized image. Then calculating root mean square error (RMS) to determine accuracy of georectified roads can help lean to determine accuracy of the vectorized features. Contingency tables are a potential to investigate if values of one variable are happening by chance in comparison to another variable (Burt et al. 2009). The Heidke skill can provide a method for assessing the agreement of the trails and paths obtained by the automatic extraction and the visual interpretation. The Heidke skill (HSS) score compares the proportion correct to the obtained no-skill forecasts (Stephenson 2000), that is, the agreement between event forecast and event observed. The range of the scores goes from negative one to one. A positive score tells us that the produced events were better than that of the already observed events, that is, the proportion correct by chance. In other the words, the produced events are the automatically extracted features and the observed events are the original hand digitized features. In the case of comparing two automatically extracted feature sets, labeling the produced and the observed becomes important. Table 1 provided below better describes the intent of using the HSS for analysis.

Event Produced	Event Observed		
	Yes	No	Marginal Total
Yes	Extracted yes & Hand Yes[1]	Extracted Yes & Hand No[2]	1+2
No	Extracted No & Hand Yes[3]	Extracted No & Hand No[4]	3+4
Marginal Total	1+3	2+4	1+2+3+4

Table 1. Example of Heidke skill score.

Equation (1) gives the calculation of the HSS and in which a is the extracted yes & Hand yes, b is the extracted yes & Hand no, c is the extracted no & Hand yes, and d is the extracted no & Hand no.

$$\mathrm{HSS} = \frac{2(\mathrm{ad}-\mathrm{bc})}{(\mathrm{a}+\mathrm{c})(\mathrm{c}+\mathrm{d})+(\mathrm{a}+\mathrm{b})(\mathrm{b}+\mathrm{d})} \tag{1}$$

A sample of four hundred random points was generated for each HSS analysis. One hundred points were drawn based on the linear features on the maps extracted from Feature Analyst and another hundred points were generated on the same maps but in the areas where there were no linear features. In the same way, two hundred points were created on the map obtained by visual interpretation and hand digitizing. Then the two sets of generated points were overlaid on the opposite extraction types. That is, random points from the Feature Analyst extraction were overlaid on the hand extracted lines and vice versa. The points were then used to complete the HSS tables.

Each individual table had 400 points assigned based on the relative location of each point in association with an extracted line. If the points from both compared maps of the extracted trails and paths were matched up on a corresponding line, the answer was a "yes, yes" match. If a point from the Feature Analyst extraction was not on a linear feature from the hand digitizing, it was a "yes, no" match and vice versa, it was a "no, yes" match. These points were further explored to see if they were one of two things: a feature that was not extracted on the hand image or a false-positive where an extraction occurred, but not trail or path existed.

It is expected that for the sample points, the automatically extracted trails and paths match the hand digitized features. It is also hopeful to produce very little to no “false-positives” in which the automatically extracted points do not produce an extracted feature that was on the hand digitized data set. Finally, to produce the optimal model for extraction, expectedly there is a high number of automatically extracted “hits” where there is no hand digitized feature, providing evidence of the potential superiority of the template matching procedure.

In this study, the comparisons being made in this table dealt with two different sets of scenarios. The first scenario was the comparison between the maps of the trails and paths from the automatic extraction and the visual interpretation and hand digitization. The second scenario was the comparisons between the maps obtained by the automatic extraction methods with different combinations of parameters including linear widths, band combinations, histogram stretches and kernel sizes/shapes.

The proposed methods above hopefully can lead to a map of military off-road vehicle trails and paths at Fort Riley, Kansas. This map can then be compared to the hand digitized map to determine the overall usefulness of the produced map. At the same time, the similar comparisons are also made between all the automatic extracted maps from the uses of different parameters. This can help lead to a proposed procedure that can be applied by the military installation land managers to update the military off-road vehicle trails and paths and to determine the need for closing and repairing of the trails and paths. It is also the hope that the developed methods can be used for extracting trails and paths in the environments other than the military installations.

CHAPTER 4

RESULTS

ENHANCMENTS/TRANSFORMATIONS

A total of twenty-four different enhancements /transformations were performed on the original color infrared image. These included: edge detection, edge enhancement, vertical edge detection, horizontal edge detection, left diagonal edge detection, right diagonal edge detection, horizontal filter, and vertical filter. These eight transformations were conducted with three different kernel sizes: 3x3, 5x5, and 7x7. This totaled 24 different image transformed and enhanced images for the study area, plus the original infrared made 25 different scenarios to run for the extraction of the military off-road trails and paths.

Figure 7 shows four enhanced/transformed images obtained using a 5x5 filter: edge detection, edge enhancement, horizontal edge detection, and vertical edge detection. Visually, the edge enhancement led to better results than the edge detection, horizontal edge detection and vertical edge detection. In Figure 8, the trails and paths could be seen on the images by the left diagonal edge detection and right diagonal edge detection images. However, the trails and paths were not clear on the images obtained by the vertical filter and horizontal filter. In addition, a lot of noise can be seen in all the images of Figures 7 and 8 except for the one obtained by the edge enhancement. Thus, the original false color infrared image and edge enhancement image were recommended for the linear feature extraction.

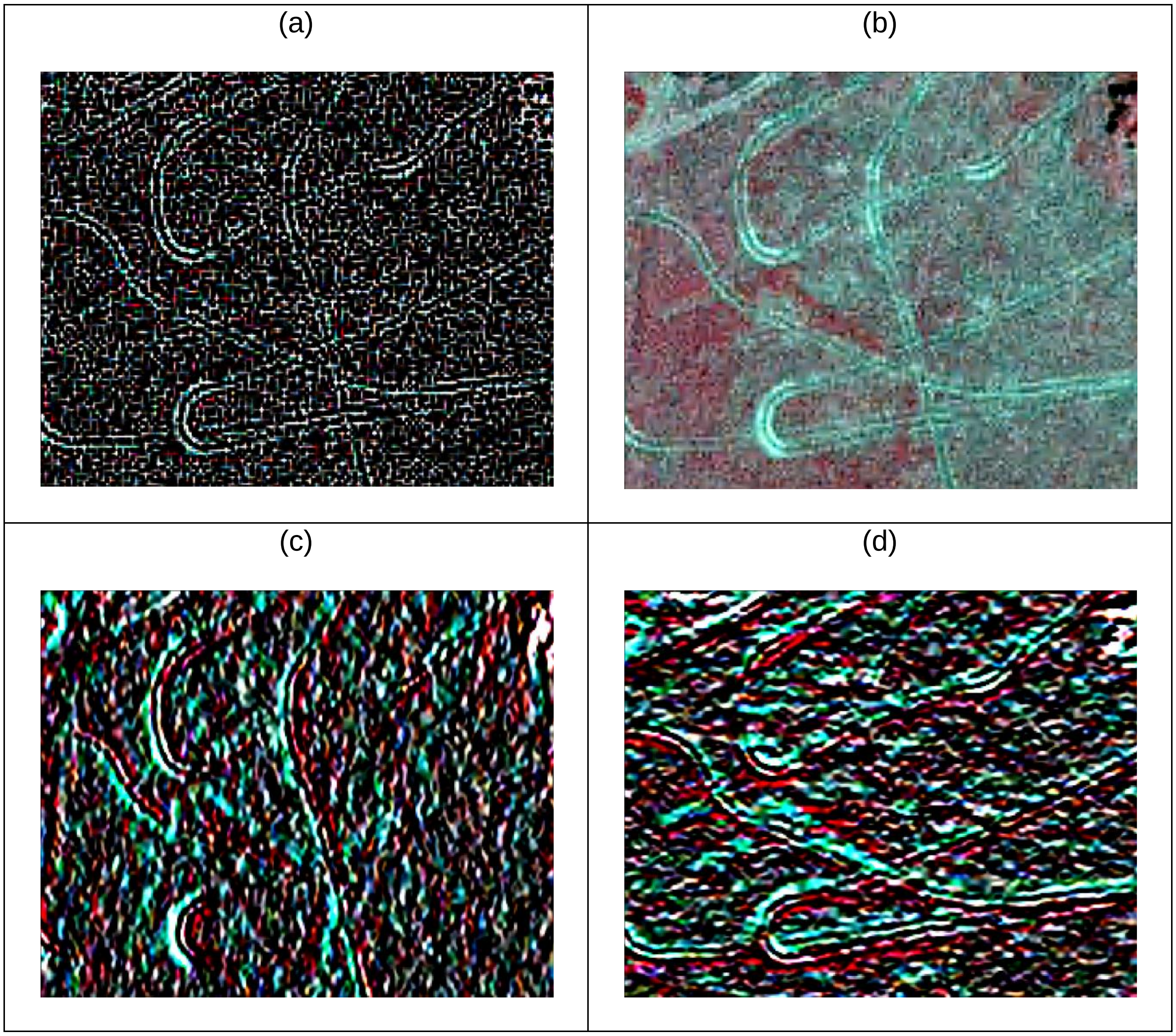

Figure 7. Enhanced/Transformed images using a 5x5 filter: a) edge detection, b) edge enhancement, c) horizontal edge detection, and d) vertical edge detection.

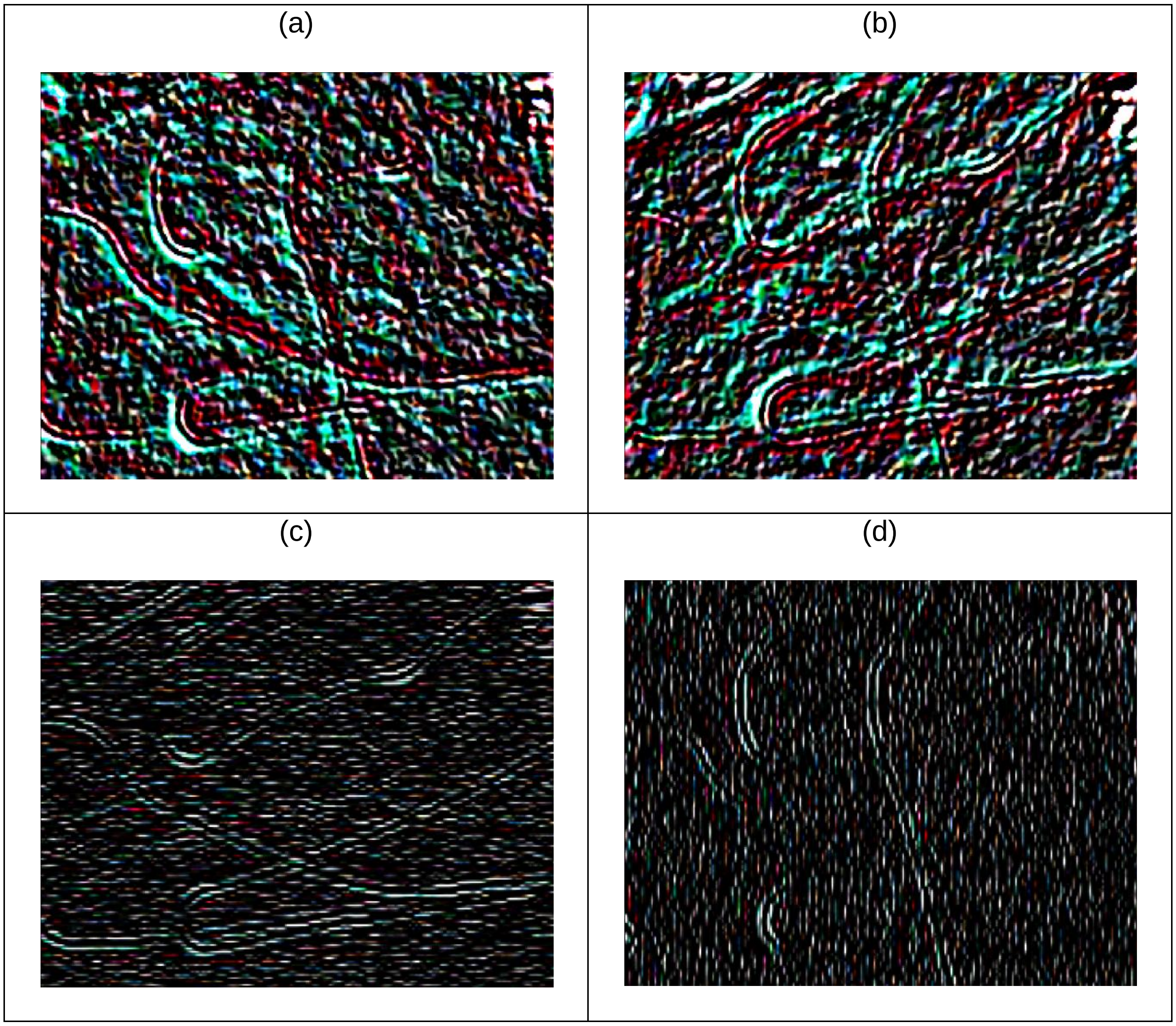

Figure 8. Enhanced/Transformed images using a 5x5 filter: a) left diagonal edge detection, b) right diagonal edge detection, c) vertical filter, and d) horizontal filter.

FEATURE EXTRACTION

The original and all twenty-four transformed and enhanced images were used to extract the military off-road vehicle trails and paths. From each of the images, three sample plots were selected based on different trails and path densities in comparison to different landscape types. Thus, a total of seventy-five sample plots were obtained. However, only seven were selected based on visual interpretation and used for the extraction of the trails and paths. Appendix C displays the feature parameters that worked best for each feature extraction based on the transformed/enhanced images.

In Figures 7 and 8, it seemed the edge detection image was not as good as the edge enhancement image, but better than other image transformations. Furthermore, the edge detection images were tested for extracting the trails and paths. It was found out that most of the edge detection filters degraded the quality of the images. For example, in Figure 9-11 everything was extracted and the trails and paths were almost not identifiable. The trail and path maps looked cluttered for all the sample plots and a lot of noise was obtained. Therefore, only the comparisons of the original false color infrared image and the edge enhancement images obtained using three filters were made.

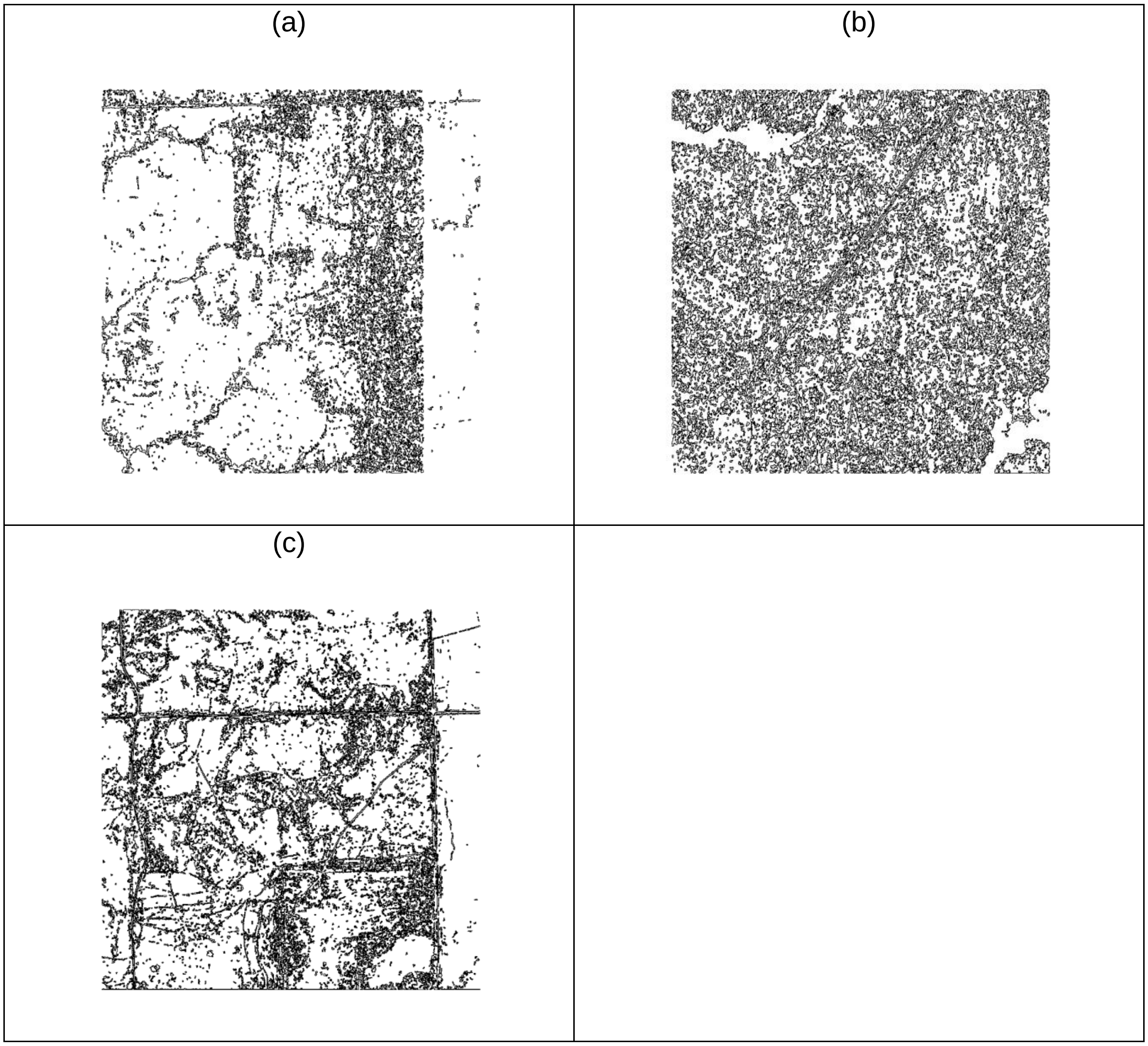

Figure 9. Linear feature extraction using the edge detection image with a 3 x 3 kernel: a) Plot 5, b) Plot 21, and c) Plot 28.

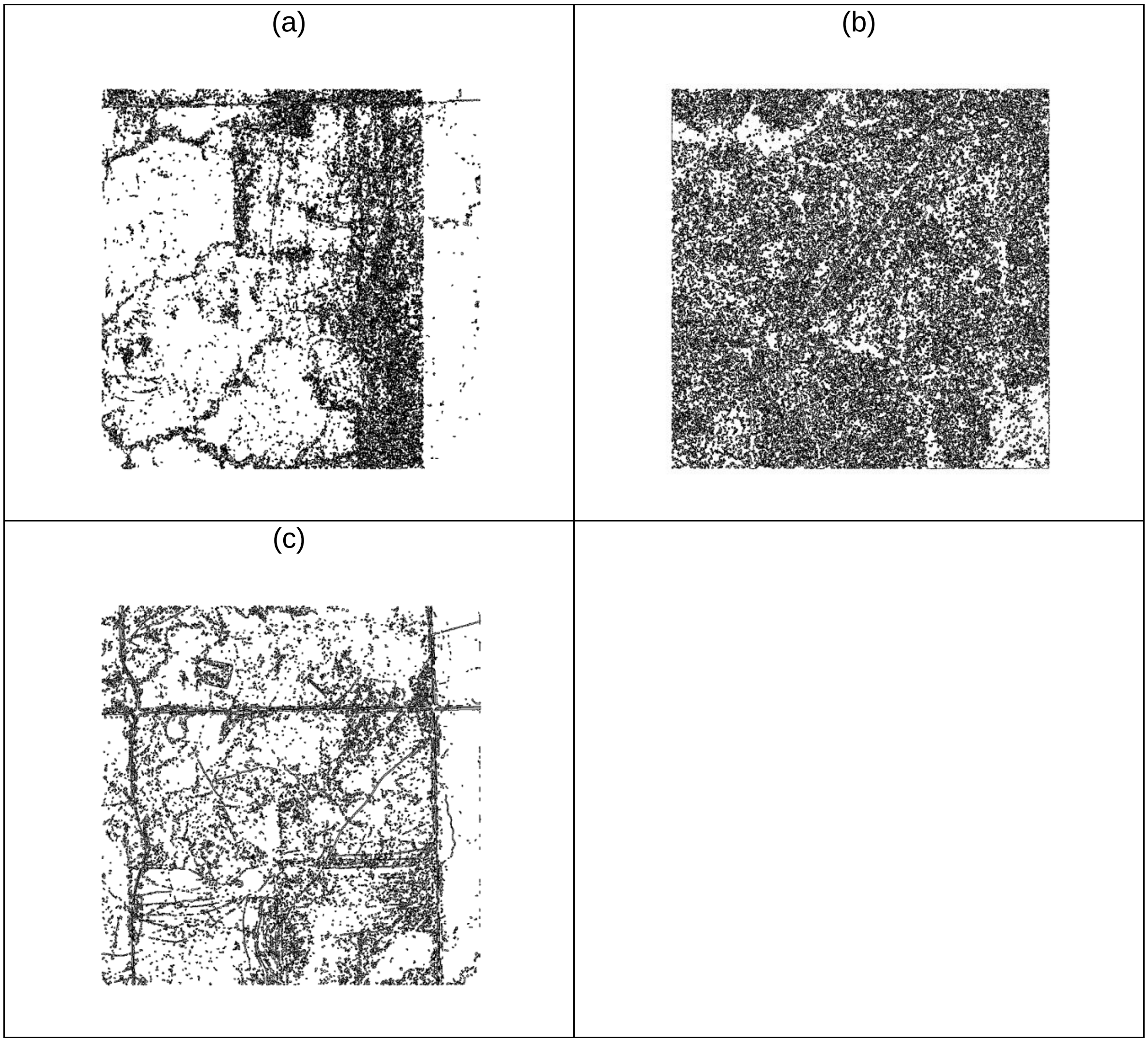

Figure 10. Linear feature extraction using the edge detection image with a 5 x 5 kernel:

a) Plot 5, b) Plot 21, and c) Plot 28.

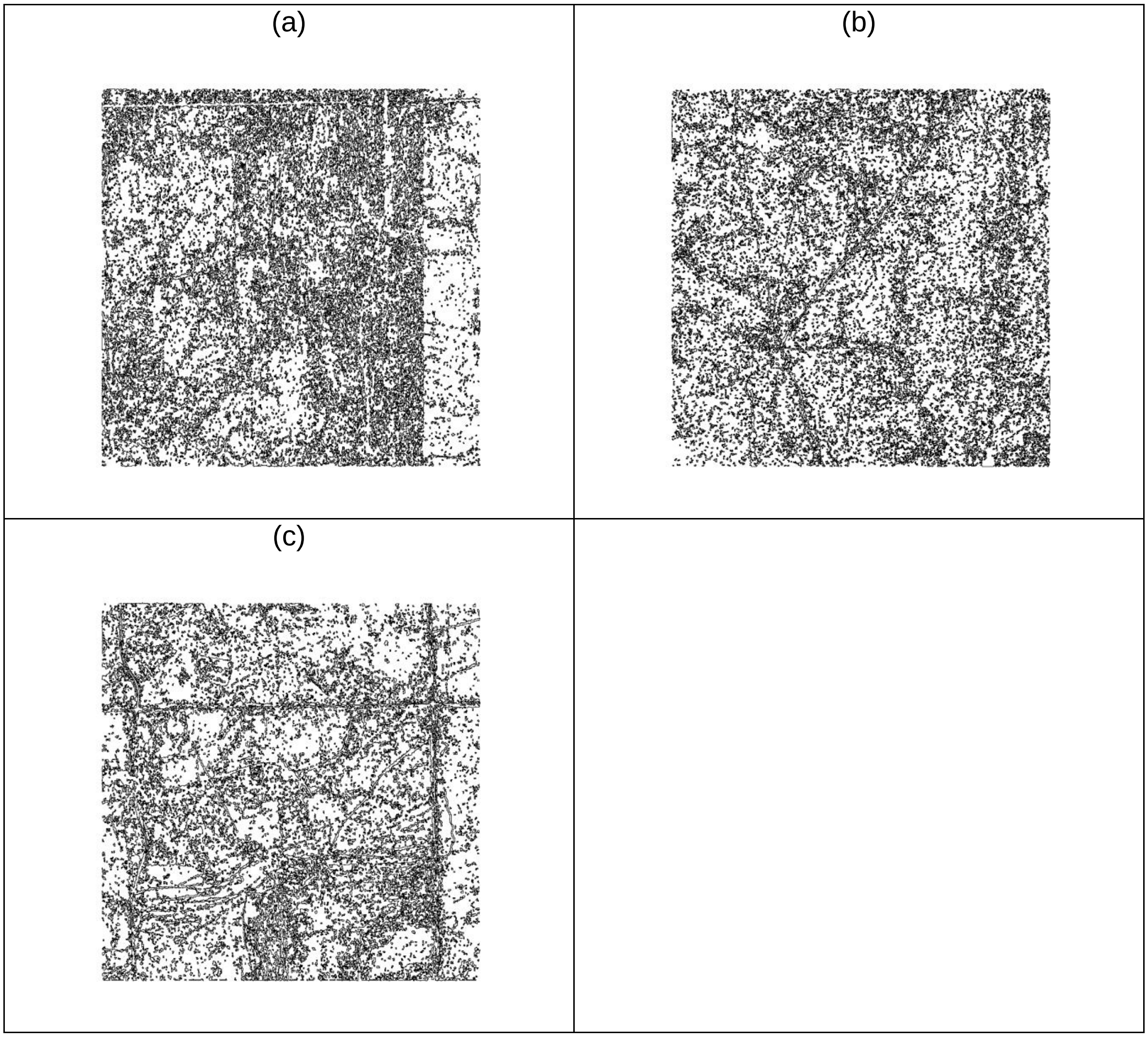

Figure 11. Linear feature extraction using the edge detection image with a 7 x 7 kernel:

a) Plot 5, b) Plot 21, and c) Plot 28.

In Figure 12, the extracted trails and paths for Plot 5 using the original false color infrared image and edge enhancement images using a 3 × 3, 5 × 5, and 7 × 7 kernel were compared and the linear features were very similar in density and spatial variability throughout the sample plot except for the image using edge enhancement using 3 × 3 kernel in which less trails and paths were captured.

In Figure 13, the extracted trails and paths of Plot 21 using the original false color infrared image were similar to those obtained using edge enhancement with a 7 × 7 kernel. The results from the edge enhancements with both 3 × 3 kernel and 5× 5 kernel were similar and more trails and paths were extracted compared to those from the original false color infrared image and the edge enhancement with a 7 × 7 kernel. In Figure 14, all four maps of the extracted trails and paths for Plot 28 using the original false color infrared image and three edge enhancements with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel looked similar.

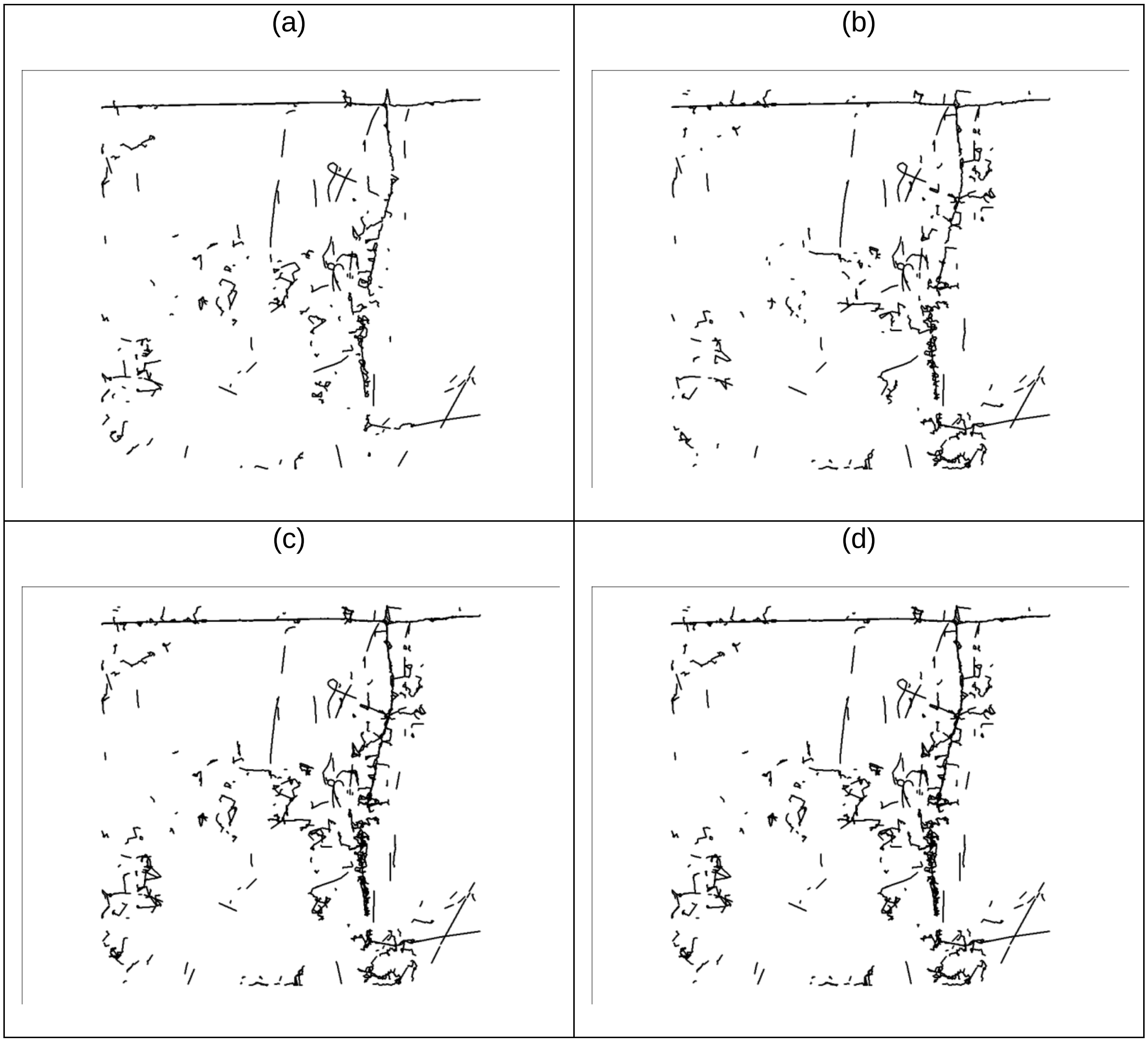

Figure 12. Comparison of the extracted trails and paths for Plot 5 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

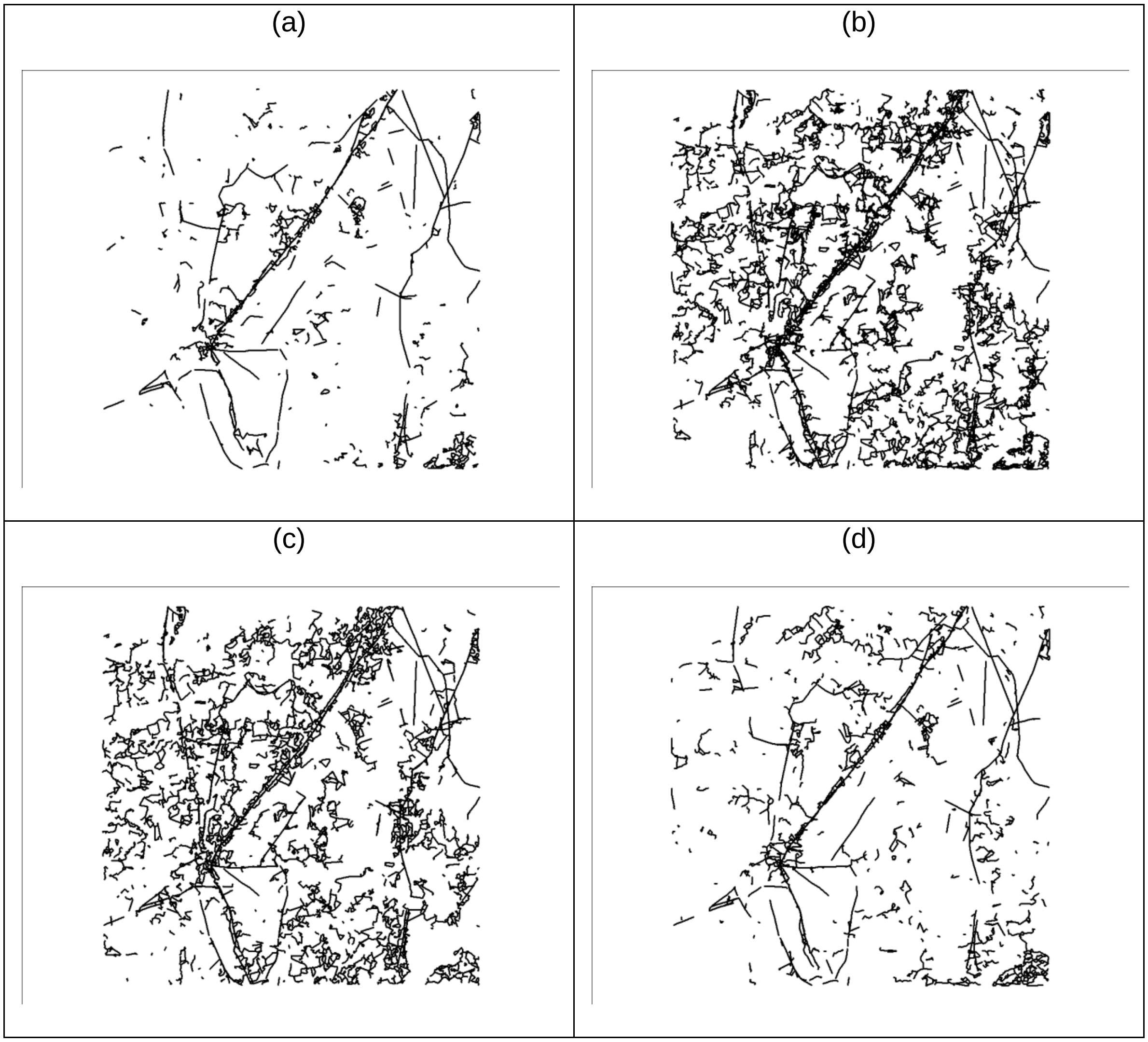

Figure 13. Comparison of the extracted trails and paths for Plot 21 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

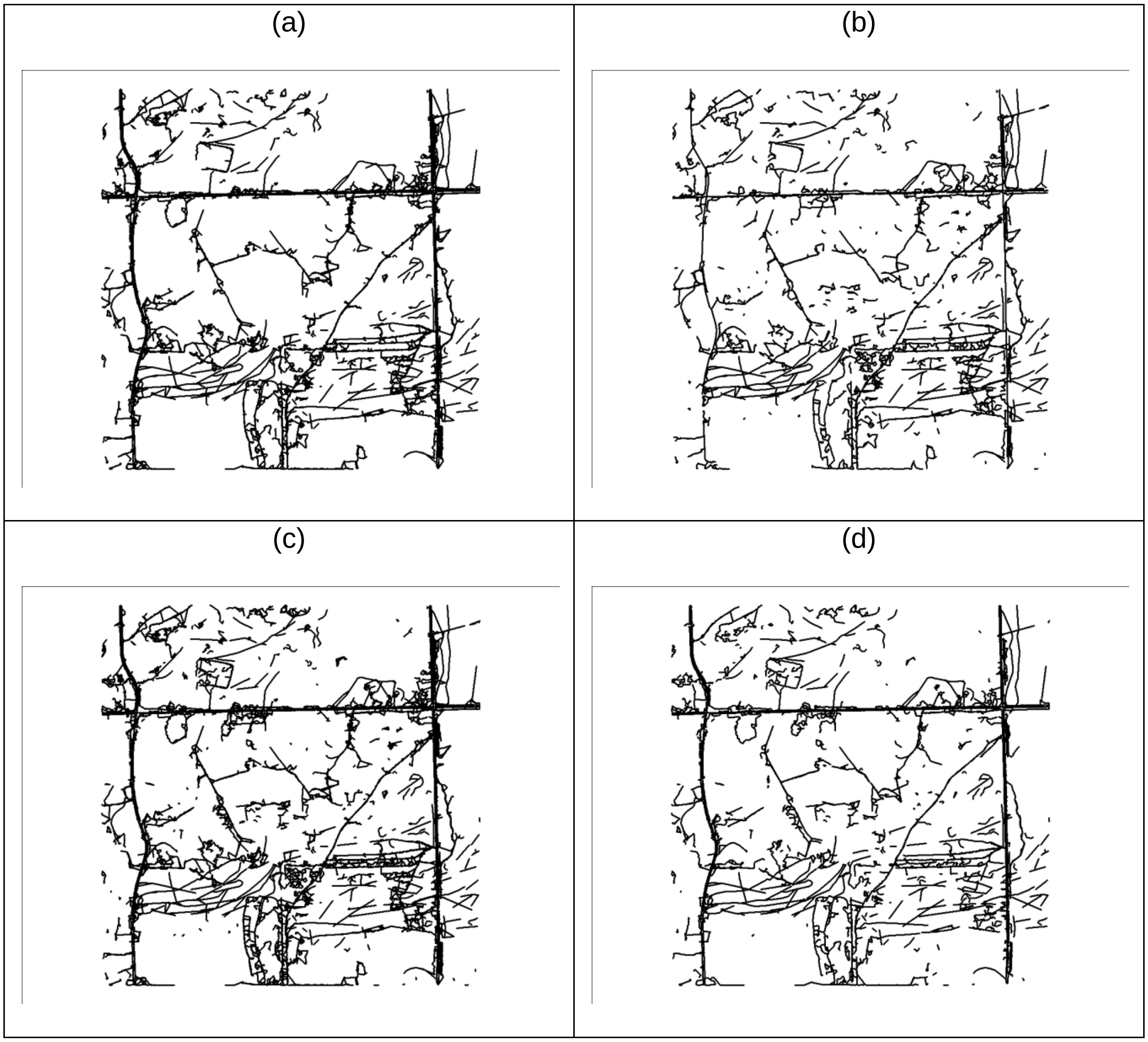

Figure 14. Comparison of the extracted trails and paths for Plot 28 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

Figures 15, 16, and 17 show the comparison of the extracted trails and paths in detail for three subsets of sample Plots 5, 21, and 28 using original false color infrared image and three edge enhancement images with a 3 x 3 kernel, a 5 x 5 kernel, and a 7 x 7 kernel. For the subset of sample plot 5 in Figure 15, similar trails and paths were extracted from three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel, while less linear features were captured from the original false color infrared image. The results were slightly different from those obtained for the entire sample plot in Figure 12.

For the subset of sample plot 21 in Figure 16, the extracted trails and paths using the original false color infrared image and the edge enhanced image with a 7 × 7 kernel were less than those from the edge enhanced images with both 3 × 3 kernel and 5 × 5 kernel. The subset of sample plot 28 in Figure 17 shows similar trails and paths extracted using the original false color infrared image and three edge enhanced images with a 3× 3 kernel, 5 × 5 kernel and 7 × 7 kernel for Plot 28. The results for these two subsets in Figures 16 and 17 were similar to those found in Figures 13 and 14 for the entire sample plots 21 and 28.

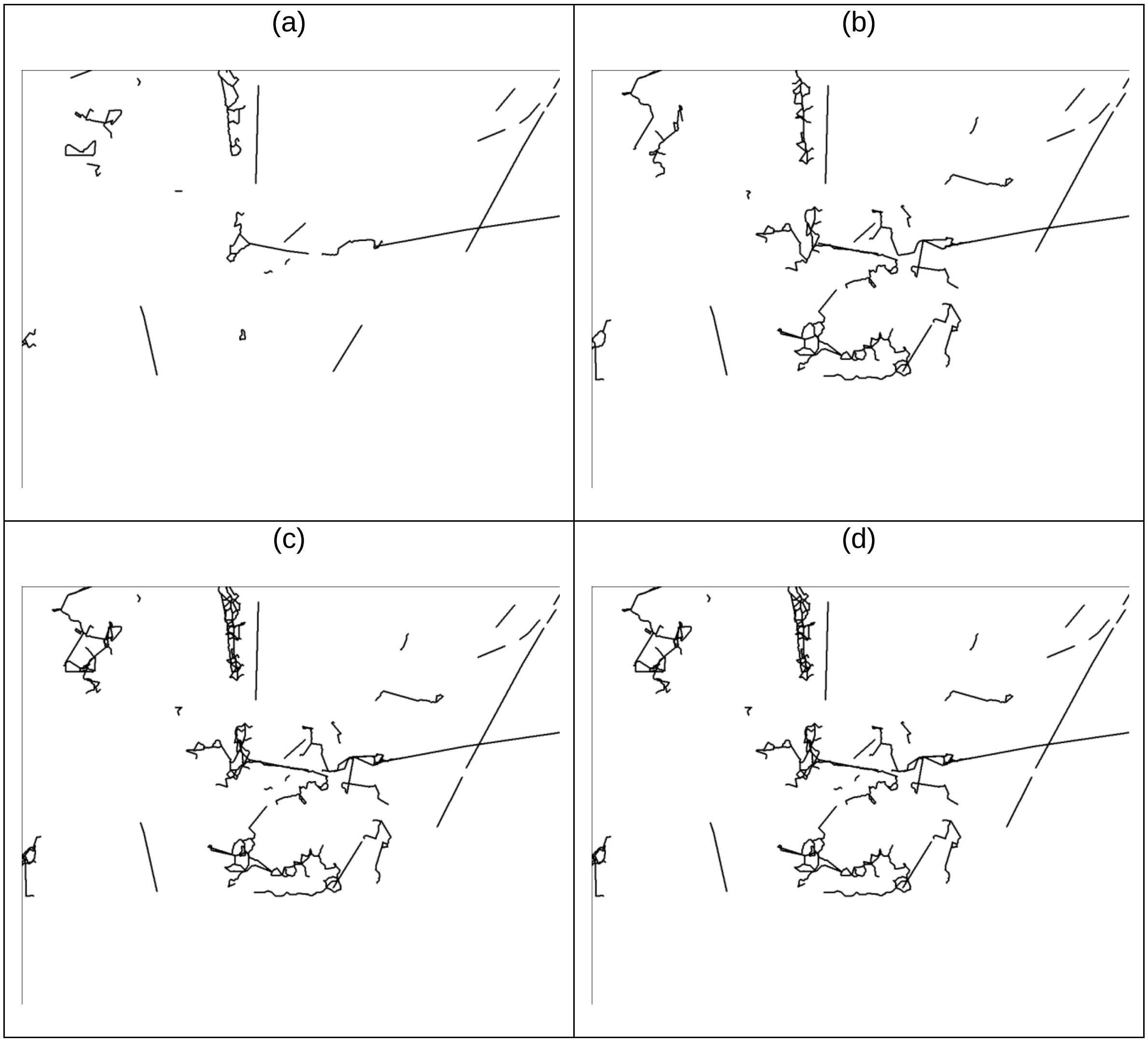

Figure 15. Comparison of the extracted trails and paths in detail for a subset of sample Plot 5 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

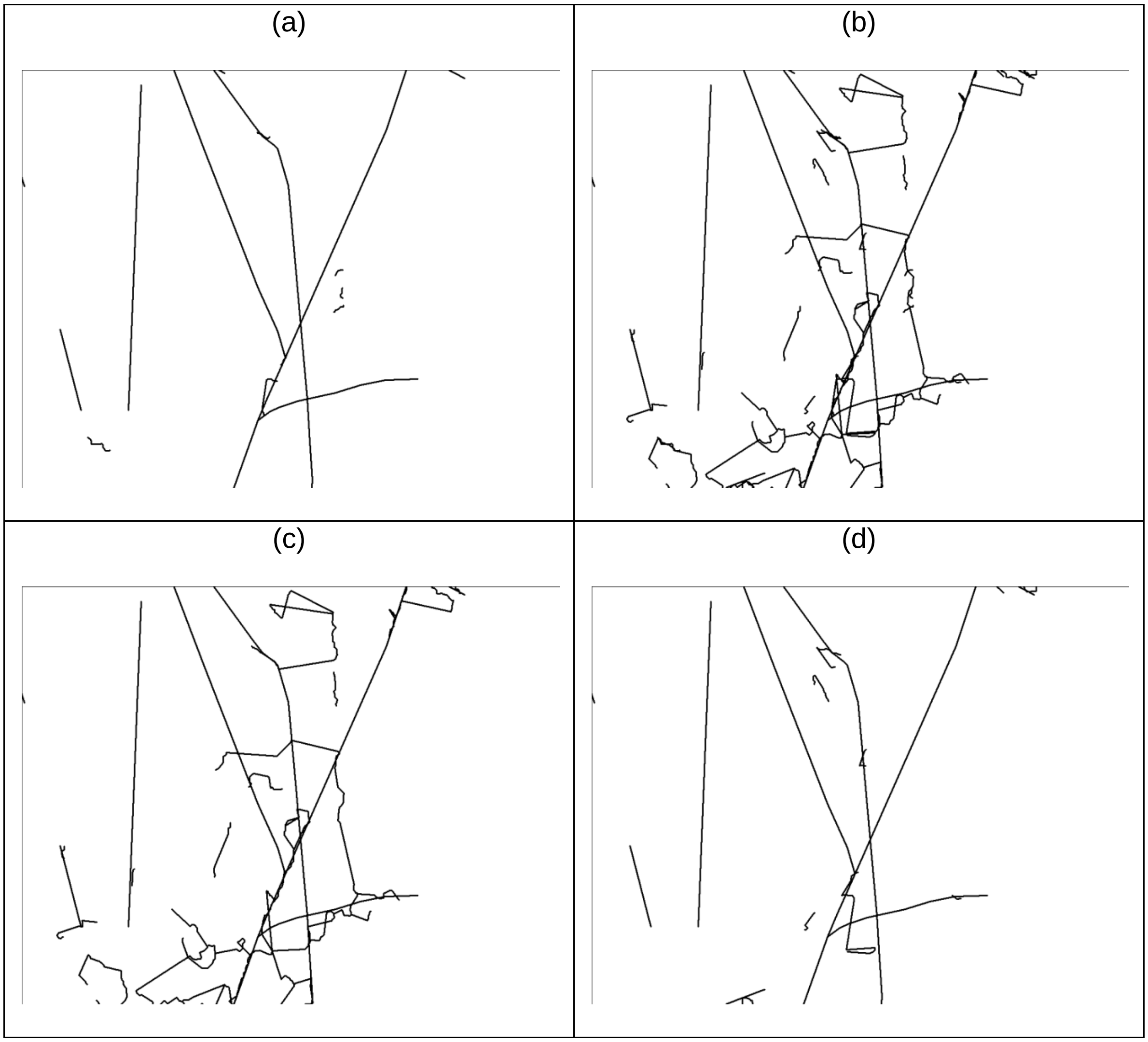

Figure 16. Comparison of the extracted trails and paths in detail for a subset of sample Plot 21 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

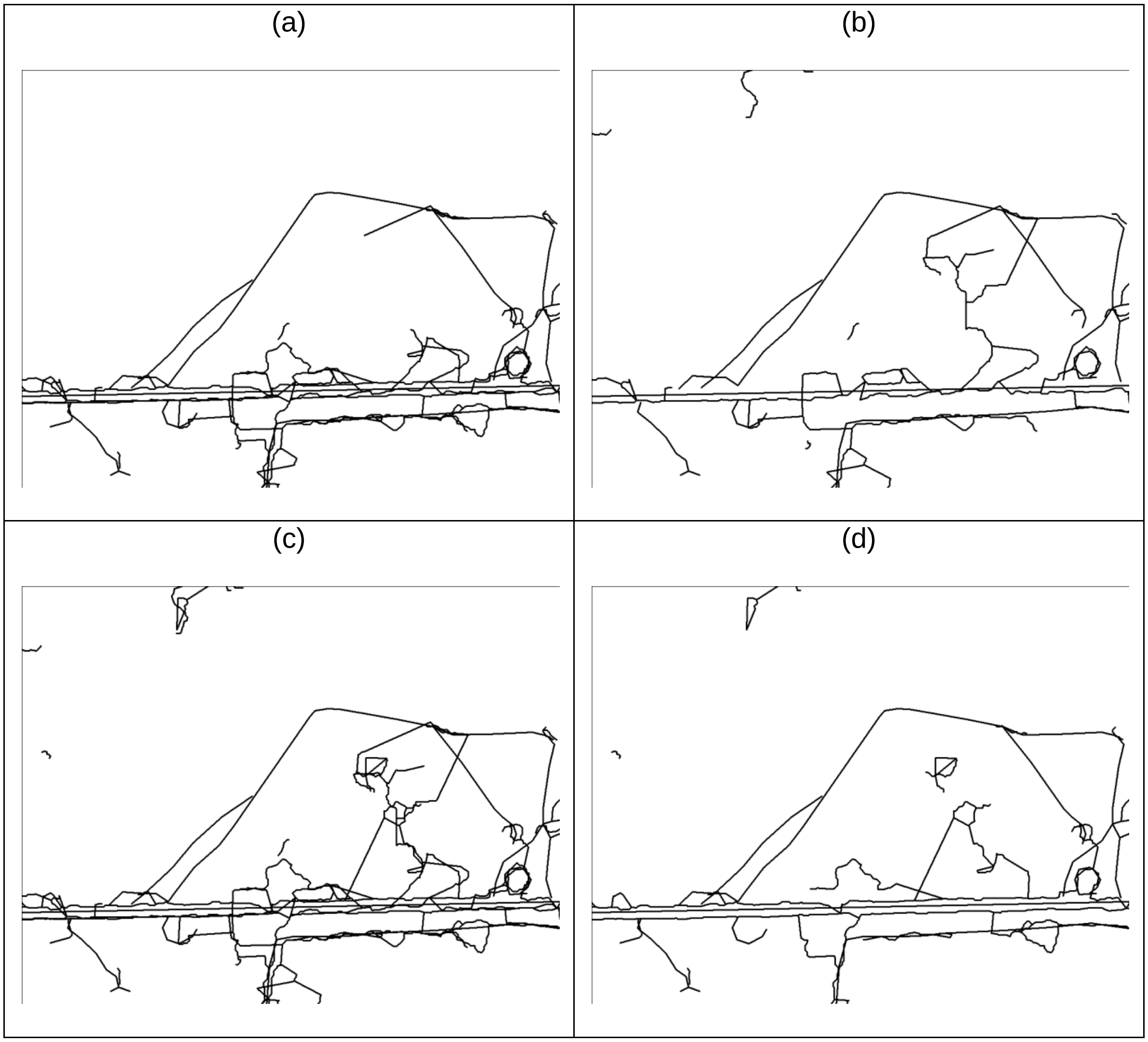

Figure 17. Comparison of the extracted trails and paths in detail for a subset of sample Plot 28 using: a) original false color infrared image and edge enhancement images with b) a 3 x 3 kernel, c) a 5 x 5 kernel, and c) a 7 x 7 kernel.

ACCURACY ASSESSMENT

For comparison, the trail and path maps from the visual interpretation and hand digitizing for sample plots 5, 21, and 28 were shown in Figure 18. Compared to the maps of trails and paths obtained by the automatic extraction in Figure 12, 13, and 14, the visual interpretation and hand digitizing led to less trails and paths. This might be because of human being limitation in visualization. In Figure 19, the trail and path maps obtained by visual interpretation and hand digitization and automatic extraction using the edge enhanced image with a 7 x 7 kernel were compared. Visually, these two maps had similar patterns, but, less trails and paths were noticed in the map from the visual interpretation and hand digitizing (Figure 19). Moreover, a total of 400 random points that were used to quantitatively assess and compare these two maps was shown in Figure 19.

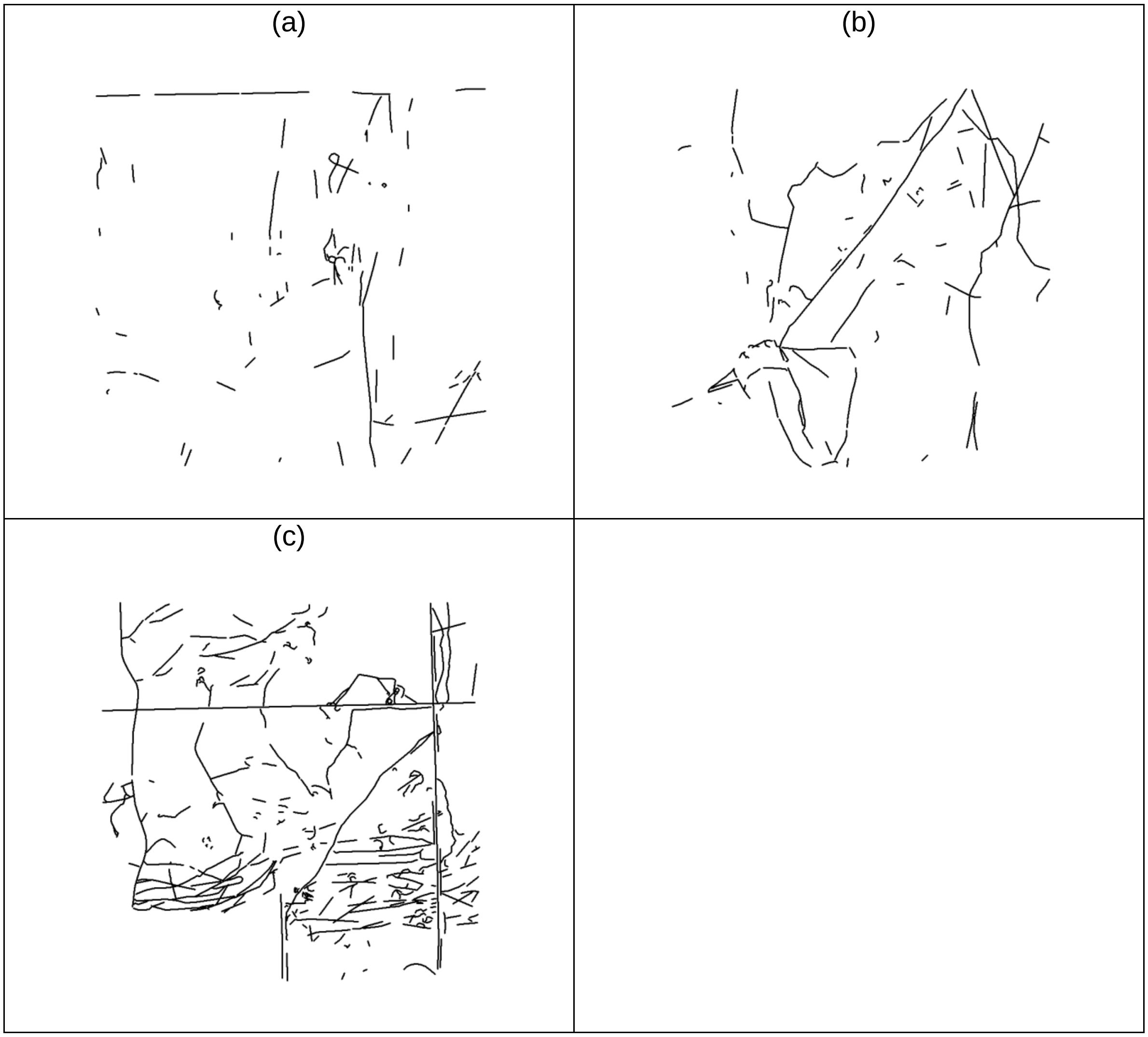

Figure 18. The trail and path maps from visual interpretation and hand digitizing for a) sample plot 5, b) sample plot 21, and c) sample plot 28 (Johnson et al. 2010).

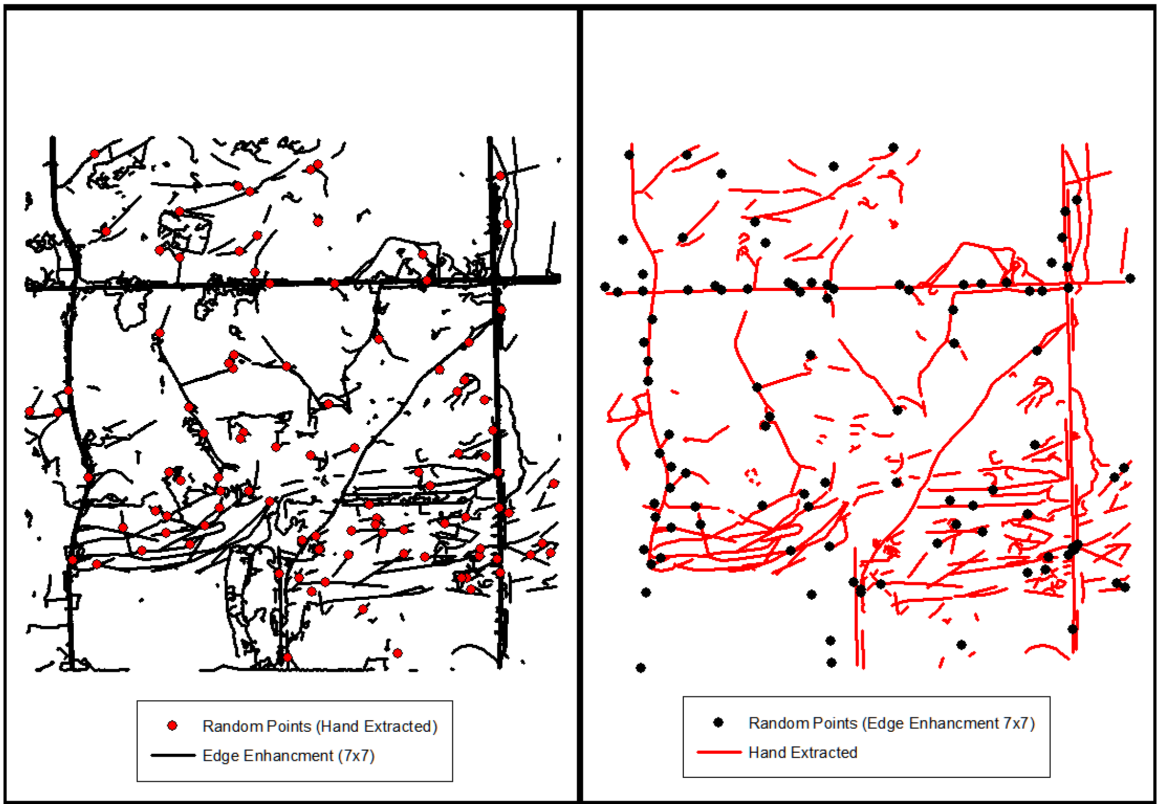

Figure 19. Random points and extracted trails and paths using the edge enhanced image with a 7 x 7 kernel and by the visual interpretation and hand digitizing.

The automatically extracted trails and paths for three sample plots and four images used: the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel, were compared with the trail and path map obtained by the visual interpretation and hand digitization. Tables 2, 3, and 4 show the match matrices for plot 5, plot 21, and plot 28, respectively, by comparing each of the trail and path maps obtained by automatic extraction using the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel with the corresponding map by the visual interpretation and hand digitization. The numbers of match (yes & yes) and non-match (no & no) varied depending on the sample plots. Overall, the edge enhanced image using a 7 × 7 kernel led to the highest numbers of match and non-match for all the three sample plots 5, 21, and 28, then the original false color infrared image, the edge enhanced image using a 5 × 5 kernel, and the edge enhanced image using a 3 × 3 kernel.

Based on Tables 2, 3, and 4, HSS scores were calculated using Equation (1) and the score results were summarized in Table 5. All the HSS scores were positive. This implied that the automatically extracting the military off-road vehicle trails and paths led to better results to those by the visual interpretation and hand digitizing for all the extractions. For plot 5, edge enhancement with a 7x7 kernel scored highest, followed by the edge enhancement with a 5x5 kernel, the edge enhancement with a 3x3 kernel, and the original infrared image scored the lowest. However, for plot 21 the original infrared image scored the highest, followed by the edge enhancement with a 7x7 kernel, the edge enhancement with a 5x5 kernel, and the edge enhancement with a 3x3 kernel scored the lowest. For plot 28, edge enhancement again scored the highest, followed by the original infrared image, then the edge enhancement with a 5x5 kernel and again the edge enhancement with a 3x3 kernel scored the lowest. Overall, the edge enhancement with a 7x7 kernel resulted in the highest HSS values, then the original infrared image, then the edge enhancement with a 5x5 kernel and the edge enhancement with a 3x3 kernel had the lowest HSS values.

Table 6 shows the Hit/Miss extraction cell that bases the extracted features from Feature Analyst on whether or not it was an extraction made based on a false/positive, such as an extracted trail that does not exist or a trail that was found to have been missed by the hand extraction.

<table>
<tr><td colspan="4">Original Infrared Plot 5</td><td colspan="4">Edge Enhancement 3x3 Plot 5</td></tr>
<tr><td rowspan="2">Event Produced</td><td colspan="3">Event Observed</td><td rowspan="2">Event Produced</td><td colspan="3">Event Observed</td></tr>
<tr><td>Yes</td><td>No</td><td>Total</td><td>Yes</td><td>No</td><td>Total</td></tr>
<tr><td>Yes</td><td>147</td><td>54</td><td>201</td><td>Yes</td><td>150</td><td>46</td><td>196</td></tr>
<tr><td>No</td><td>8</td><td>191</td><td>199</td><td>No</td><td>13</td><td>191</td><td>204</td></tr>
<tr><td>Total</td><td>155</td><td>245</td><td>400</td><td>Total</td><td>163</td><td>237</td><td>400</td></tr>
<tr><td colspan="4">Edge Enhancement 7x7 Plot 5</td><td colspan="4">Edge Enhancement 5x5 Plot 5</td></tr>
<tr><td rowspan="2">Event Produced</td><td colspan="3">Event Observed</td><td rowspan="2">Event Produced</td><td colspan="3">Event Observed</td></tr>
<tr><td>Yes</td><td>No</td><td>Total</td><td>Yes</td><td>No</td><td>Total</td></tr>
<tr><td>Yes</td><td>171</td><td>33</td><td>204</td><td>Yes</td><td>158</td><td>43</td><td>201</td></tr>
<tr><td>No</td><td>4</td><td>192</td><td>196</td><td>No</td><td>6</td><td>193</td><td>199</td></tr>
<tr><td>Total</td><td>175</td><td>225</td><td>400</td><td>Total</td><td>164</td><td>236</td><td>400</td></tr>
</table>

Table 2. Skill score tables for plot 5 by comparing each of the trail and path maps obtained by automatic extraction using the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel with the corresponding map by visual interpretation and hand digitization.

Original Infrared Plot 21				Edge Enhancement 3x3 Plot 21			
Event Produced	Event Observed			Event Produced	Event Observed		
	Yes	No	Total		Yes	No	Total
Yes	170	32	202	Yes	153	71	224
No	4	194	198	No	5	171	176
Total	174	226	400	Total	158	242	400
Edge Enhancement 7x7 Plot 21				Edge Enhancement 5x5 Plot 21			
Event Produced	Event Observed			Event Produced	Event Observed		
	Yes	No	Total		Yes	No	Total
Yes	150	55	205	Yes	153	65	218
No	3	192	195	No	1	181	182
Total	153	247	400	Total	154	246	400

Table 3. Skill score tables for plot 21 by comparing each of the trail and path maps obtained by automatic extraction using the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel with the corresponding map by visual interpretation and hand digitization.

Original Infrared Plot 28				Edge Enhancement 3x3 Plot 28			
Event Produced	Event Observed			Event Produced	Event Observed		
	Yes	No	Total		Yes	No	Total
Yes	171	29	200	Yes	168	37	205
No	8	192	200	No	4	191	195
Total	179	221	400	Total	172	228	400
Edge Enhancement 7x7 Plot 28				Edge Enhancement 5x5 Plot 28			
Event Produced	Event Observed			Event Produced	Event Observed		
	Yes	No	Total		Yes	No	Total
Yes	184	21	205	Yes	171	39	210
No	6	189	195	No	2	188	190
Total	190	210	400	Total	173	227	400

Table 4. Skill score tables for plot 28 by comparing each of the trail and path maps obtained by automatic extraction using the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel with the corresponding map by visual interpretation and hand digitization.

Extraction Image	Kernel	Plot	HSS
Original Infrared	-	5	0.690348358
Original Infrared	-	21	0.820233696
Original Infrared	-	28	0.815
Edge Enhancement	3x3	5	0.703904446
Edge Enhancement	3x3	21	0.629340616
Edge Enhancement	3x3	28	0.795714998
Edge Enhancement	5x5	5	0.755220302
Edge Enhancement	5x5	21	0.676692466
Edge Enhancement	5x5	28	0.796374472
Edge Enhancement	7x7	5	0.815461347
Edge Enhancement	7x7	21	0.711693799
Edge Enhancement	7x7	28	0.865168539

Table 5. Summary of HSS scores for the automatically extracted trails and paths for three sample plots and four images used: the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel, compared with the trail and path map obtained by visual interpretation and hand digitization.

Extraction Image	Kernel	Plot	Hit/Miss	Hit	Miss	% Hit
Original Infrared	-	5	54	36	18	66.66
Original Infrared	-	21	32	8	24	25.00
Original Infrared	-	28	29	21	8	72.41
Edge Enhancement	3x3	5	46	25	21	54.35
Edge Enhancement	3x3	21	71	36	35	50.70
Edge Enhancement	3x3	28	37	14	23	37.84
Edge Enhancement	5x5	5	43	22	21	51.16
Edge Enhancement	5x5	21	65	16	49	24.62
Edge Enhancement	5x5	28	39	18	21	46.15
Edge Enhancement	7x7	5	33	26	7	78.79
Edge Enhancement	7x7	21	55	20	35	36.36
Edge Enhancement	7x7	28	21	10	11	47.62

Table 6. Summary of "Hit/Miss" ratios for the automatically extracted trails and paths for three sample plots and four images used: the original false color infrared image and three enhanced images with a 3 × 3 kernel, 5 × 5 kernel, and 7 × 7 kernel, compared with the trail and path map obtained by visual interpretation and hand digitization.

CHAPTER 5

DISCUSSION AND CONCLUSIONS

RESULTS REVISTED

Compared to the visual interpretation and hand digitizing, overall, the automatic extraction algorithm led to more military off-road vehicle trails and paths. All the HSS scores were considerably above the zero thresholds (Table 5), which means that most of the automatically extracted results were matches to the hand digitized results. But, this does not necessarily mean that the accuracy of the automatically extracted trails and paths were good or bad. Two interesting findings were obtained. The edge enhancement with a 7x7 kernel tended to have higher HSS values than the rest of the extraction images and the edge enhancement with a 3x3 kernel tended to have the lowest HSS values. This could be that a kernel with a small width could not capture the width of the trails and paths and that a wider kernel should be used to make sure that all trails and paths fit inside the kernel's moving window. This allowed for a more in-depth analysis into the automatic extraction results that were produced in Table 6. Each percentage found under the "% Hit" heading was the total percentage of the random points that were found to be extracted results that the hand extracted missed. Looking at the extracted results visually, HSS scores, and percent Hit/Miss scores did not reveal anything of great value for which extractions were best. They did prove that the Feature Analyst captured more trails/paths than the visual interpretation and hand digitizing, but also produced false-positive extractions.

SUGGESTIONS FOR PROPOSED METHODS

In this study, automatically extracting the military off-road vehicle trails and paths at Fort Riley installation was conducted using ERDAS Imagine and ESRI's ArcGIS suite with Overwatch Geospatial's Feature Analyst 5.0 extension and a 0.5 meter resolution false color infrared image and following suggestions can be obtained based on the evidence gathered. First of all, performing geometric and radiometric corrections is always necessary in terms of a better quality of images with a desired coordinate system. Secondly, when ERDAS Imagine was used for image transformations and enhancements, there was obvious evidence that indicates the edge enhancement algorithm can result better quality of images for automatic extraction of the trails and paths. On the other hand, it was clear that the edge detection filters did not work well in this study. But, utilizing an edge enhancement filter with a kernel size of 5 x 5 seemed to be able to create a similar trail and path map to the visual interpretation and hand digitizing. Moreover, selecting the interest areas from the images that had the trails and paths may affect the assessment of accuracy. Trying to select the areas that had less trails and paths may make the program run more efficiently, but would produce a false accuracy. Finally, selecting a proper feature parameter for the template matching/machine learning approach would have a great impact on the results of extracting the trails and paths.

RESEARCH QUESTIONS AND HYPOTHESES REVISTITED

This study answered the research questions and hypotheses very well. The first question was "Can the military off-road vehicle trails and paths be identified on high resolution images and efficiently extracted via linear extraction method: template matching and machine learning approach?" The hypothesized answer was yes. The results concluded that this was true. However, it does deserve some specifications on how and why. The spatial resolution of the image is one of the most important factors that have impacts on the accuracy of the extracted trails and paths. The 0.5 meter spatial resolution was good enough in identifying the military off-road vehicle trails and paths. However the high spatial resolution of the image caused problems with the feature extraction. The initial idea was to extract the trails and paths for the entire image. But, it was not successful due to the large size of the image and great amount of member required. Thus, in this study three sample plots that had different landscape and trail/path densities were selected and used to extract the trails and paths. This allowed for quicker processing time and a more accurate feature extraction.

The second question was "What spectral transformations can best enhance the interpretation of off-road vehicle trails and paths in this study area?" The hypothesized answer was an edge detection filter with a kernel size of 5x5. This proved to be incorrect. The edge detection filters degraded the image to a degree that the extractions were inaccurate. Instead, the edge enhancement algorithm was better than all the other image transformations. Among the kernel sizes used, 3 x 3, 5 x 5, and 7 x 7, it was found out the kernel size 7 x 7 best captured the trails and paths. This is believed because of the different landscape types and different ages of the trails and paths throughout the study area to be affected differently from the kernel sizes. But, the kernel sizes less 7 x 7 seemed to too small. As discussed before, the intermittent trails and paths throughout the study area (See Appendix B) have caused problems for extraction.

The third question was “Will the same combination of feature parameters work best for all image transformations/enhancements??" The hypothesized answer was that the same combination of feature parameters will work best for all image transformations/enhancements. The histogram stretch, kernel pattern, and kernel pattern size all proved to be different for each image transformation/enhancement and for each sample area. There was no consistency between the different sample plots and the associated transformation/enhancement.

The final question was "Is the semi-automatic and automatic extraction of the off-road vehicle trails and paths better than the visual interpretation/hand digitization?" The hypothesized answer was that the semi-automatic and automatic approaches would indeed lead to better extraction than the visual inspection. This was subjective. The results show that the semi-automatic and automatic approaches did extract more trails and paths than the hand digitizing, but it also extracted the features that were not trails and paths. The HSS scores were all positive and the edge enhancement with a 7x7 kernel had the highest scores for plots 5 and 28 and the original infrared image had the highest score for plot 21. In addition, the visual interpretation and hand digitizing is very much time-consuming compared to the automatic extraction algorithm. The major problem for the automatic extraction algorithm is it output some things that were not trails and paths at all.

OTHER ASPECTS

Linear feature extraction sometimes works well with a simple image that has not been transformed. The human being, with common knowledge and a little training, can interpret what a computer system does on an aerial photo. However, when dealing with efficiently exacting linear features, computes become more powerful and favorite because they allows for various image enhancements and transformations towards improvement of image quality. On the other hand, the imagery always plays an important role in successful extractions of linear features in terms of their spatial, spectral, and radiometric resolutions.

This study provided the results of the military off-road vehicle trails and paths for Fort Riley installation. However, the proposed methods can also be applied to extracting similar linear features of this particular low brush landscape. In this study, a template matching/machine learning approach was used to extract the trails and paths and it provided an insight into possible methods for effective extraction of general linear features.

In this study, the used image consisted of three bands including green, red, and near infrared and had a 0.5 meter spatial resolution. The multispectral and high spatial resolution image provided enough details and contrast so that it allowed for identification of even the most obscure trails and paths. However, this multispectral and high spatial resolution image led to a need of a large amount of time and patience for image transformations and extraction of the trails and paths although the used software – ERDAS imagine and its extensions - Feature Analyst were most powerful and the study area was relatively small. This implied a strong need of more powerful computer hardware and software systems for a large study area.

The complexity of the landscape and the trails and paths may also affect the extraction of the trails and paths. The used image had a relatively simple landscape and a lot of uniformity, but the trails and paths had complicated structures including variable directions and densities, and great spatial variability (Appendix B). All these might increase the difficulty to extract the trails and paths for the entire image. This was why in this study several sample plots were selected to test the Feature Analyst program at Fort Riley, which provided the potential to develop a methodology for extracting the trails and paths for the entire study area.

Furthermore, in this study it was found that the combinations of feature parameters that worked best varied depending on the different sample plots selected. For example, the best image enhancement and transformation was different from sample plot to another. The used Feature Analyst provided a way to automatically select the best fit parameters for a particular area of interest. Histogram stretches of Standard Deviation and Minimum-Maximum were two feature parameters selected for the sample plots. Four different search kernels were selected: including Bull's Eye one, two, four and Manhattan (Figure 20) and pattern widths ranged from seven to thirteen in odd increments.

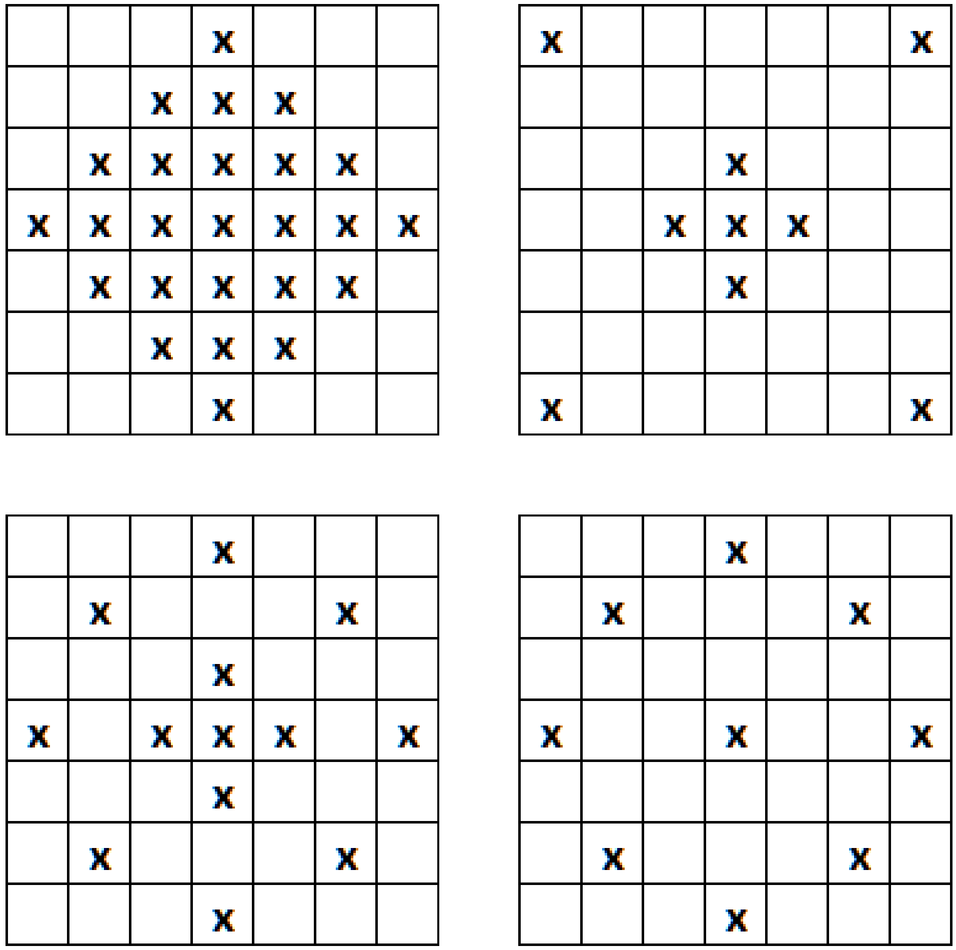

Figure 20. Different kernel patterns with pattern widths of seven starting top left going clockwise: Manhattan, Bull's Eye 1, Bull's Eye 3, and Bull's Eye 4.

The biggest contributor to the different combinations of feature parameters for different sample plots was the complexity of the trails and paths. Most of the trails and paths were fairly similar in width. But, nothing was similar in their direction, density, and spatial variability. The trails and paths went in all directions and even circular at times. The variable directions of the trails and paths caused the problems in eliminating the false-positive extractions. This caused the distress in creating templates efficiently to cover the basics of each sample plot. The density of the trails also varied greatly throughout the image. There was, as discussed earlier (Appendix B), plenty of area at Fort Riley that had no trails and paths at all. Some areas had a few tank trails, while other areas had a massive amount of trails and paths. This not only caused the problem to create templates but also led to the generation of false trails and paths. On the other hand, some trails and paths had high contrast between the dirt trails/paths and their surrounding vegetation on the landscape. Other trails and paths would be faded away. The contrast also greatly changed along the trails and paths. A trail or path could have higher contrast at one point, but to fade out a few meters away and then went back to a higher contrast again. All these would complicate the automatic extraction of the military off-road vehicle trails and paths at Fort Riley.

FUTURE STUDIES

The future studies of linear feature extraction are of great importance. However, there is still a gap from true automatic extraction of military off-road vehicle trails and paths. This is partly because of fewer reports that have existed in this area and partly because the trails and paths are more complicated in terms of their structures including variable direction and density and spatial variability compared to general linear features such as streets. For the purpose, the focus has to be put largely on spatial, spectral, and radiometric resolutions of the imagery. Moreover, focus also has also to be put on the algorithms that can be used to detect these trails and paths in terms of variable directions and density and spatial variability of the linear features. In addition, image transformations and enhancements also provide the potential to improve the extraction of the trails and paths.

Kaiser et al. (2004) and Witzum and Stow (2004) provided examples of trail and paths extraction via a machine learning and template matching approach. Both suggested techniques for dealing with the linear features that blend with the surrounding landscape. However, they did not propose approaches for advanced statistical analysis for evaluating the extracted linear features. Peteri et al. (2004) went into great detail of accurately assessing linear features extracted from high resolution imagery. The process involves having several different persons extracting the linear features and using complex trigonometry to create buffer zones for accuracy checking. Radiometric profiles are used for accuracy checking as well as the features themselves. This study used HSS score and provided an alternative for the accuracy analysis of extracted trails and paths. This method can be used to accuracy assessment of general linear features.

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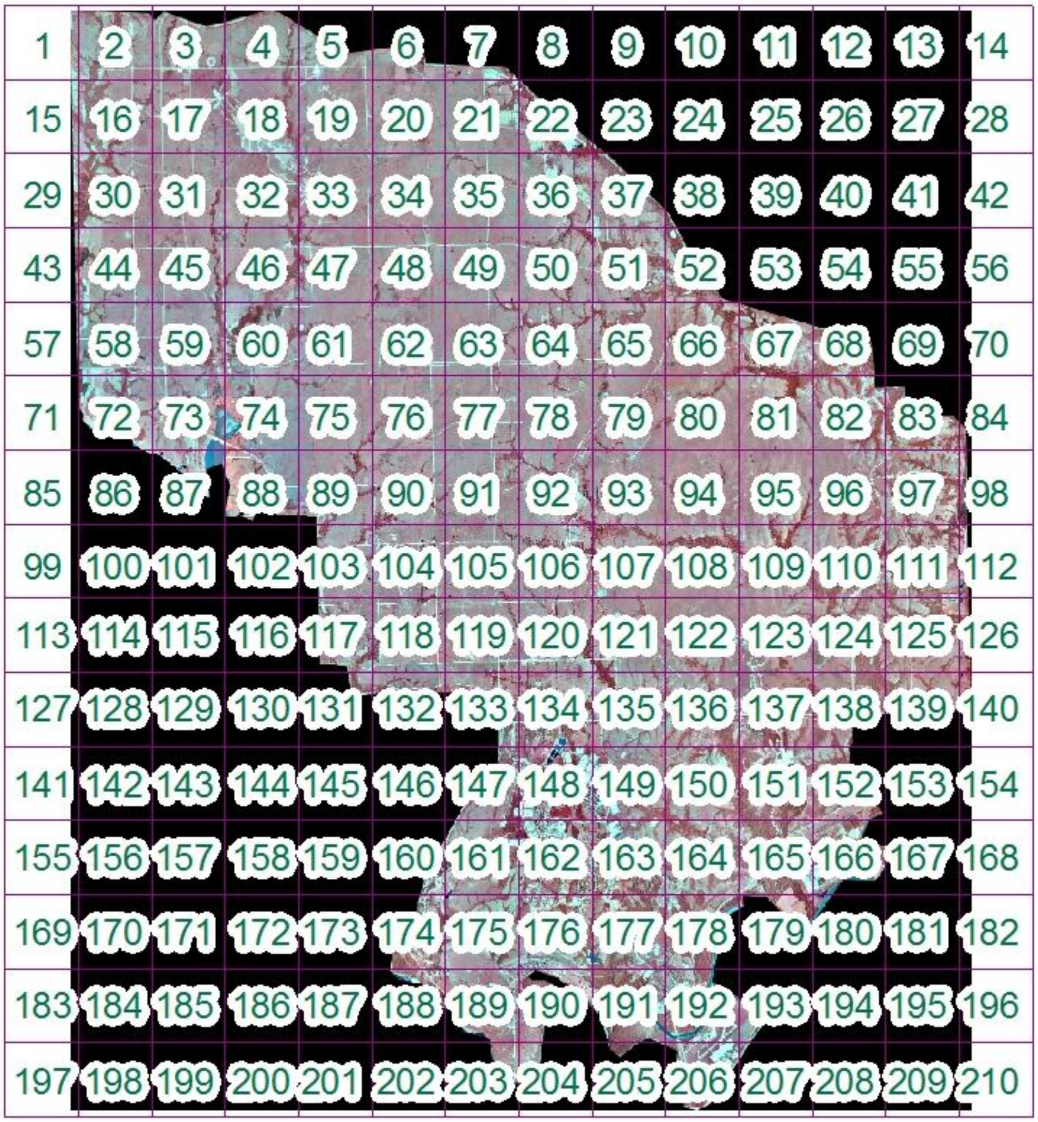
Appendices

Appendix A. 2000 meter grid sections over the original infrared image.



Appendix B. Grid Sections that have trails/paths or no trails/paths.

1	2	3	4	5	6	7	8	9	10	11	12	13	14
15	16	17	18	19	20	21	22	23	24	25	26	27	28
29	30	31	32	33	34	35	36	37	38	39	40	41	42
43	44	45	46	47	48	49	50	51	52	53	54	55	56
57	58	59	60	61	62	63	64	65	66	67	68	69	70
71	72	73	74	75	76	77	78	79	80	81	82	83	84
85	86	87	88	89	90	91	92	93	94	95	96	97	98
99	100	101	102	103	104	105	106	107	108	109	110	111	112
113	114	115	116	117	118	119	120	121	122	123	124	125	126
127	128	129	130	131	132	133	134	135	136	137	138	139	140
141	142	143	144	145	146	147	148	149	150	151	152	153	154
155	156	157	158	159	160	161	162	163	164	165	166	167	168
169	170	171	172	173	174	175	176	177	178	179	180	181	182
183	184	185	186	187	188	189	190	191	192	193	194	195	196
197	198	199	200	201	202	203	204	205	206	207	208	209	210

White: Trails/Paths; Grey: No Trails/Paths

Appendix C. Feature Analyst's automatically selected attributes for detecting trails and paths

Image	Sample Plot Location	Histogram Stretch	Pattern	Pattern Width
Edge Detection 5x5	5	Min-Max	Bull's Eye 2	7
Edge Detection 5x5	21	Std Dev	Manhattan	9
Edge Detection 5x5	28	Min-Max	Bull's Eye 4	13
Edge Enhance 5x5	5	Std Dev	Manhattan	9
Edge Enhance 5x5	21	Std Dev	Bull's Eye 4	13
Edge Enhance 5x5	28	Min-Max	Bull's Eye 2	11
Original Infrared	5	Std Dev	Bull's Eye 4	13
Original Infrared	21	Min-Max	Bull's Eye 1	11
Original Infrared	28	Std Dev	Bull's Eye 4	13
Edge Detection 3x3	5	Std Dev	Manhattan	9
Edge Detection 3x3	21	Std Dev	Bull's Eye 2	11
Edge Detection 3x3	28	Std Dev	Manhattan	9
Edge Detection 7x7	5	Std Dev	Manhattan	7
Edge Detection 7x7	21	Std Dev	Manhattan	9
Edge Detection 7x7	28	Std Dev	Manhattan	9
Edge Enhance3x3	5	Min-Max	Bull's Eye 4	13
Edge Enhance3x3	21	Std Dev	Bull's Eye 4	13
Edge Enhance3x3	28	Std Dev	Bull's Eye 4	13
Edge Enhance 7x7	5	Min-Max	Bull's Eye 2	11
Edge Enhance 7x7	21	Std Dev	Bull's Eye 2	11
Edge Enhance 7x7	28	Min-Max	Bull's Eye 1	11