An Automated Change Detection System for Specific Features

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Monitoring change through remote sensing has numerous applications, such as monitoring agricultural lands, mapping noxious weeds, disaster monitoring, ecosystem monitoring, fire detection, and countless other applications. Currently, detecting changes of specific features between imagery over time is a slow, labor-intensive, painful, and costly process. Previous attempts to automate this process do not provide accurate enough information. This paper presents the first viable system for automating the target-specific change-detection process. Results on several datasets show our technique is accurate at extracting only changes of interest, saves a considerable amount of labor, has a simple user interface, and works directly within ArcGIS.

Introduction

There is a critical need for intelligent change detection algorithms and geoprocessing techniques for digital imagery archives. Currently, the change detection process is slow, labor-intensive, and costly. Automations in the change detection system would facilitate rapid geospatial database development and have many valuable applications, including but not limited to land-cover and land-use change analyses, ecosystem monitoring, and global awareness. Change detection methods that rely on pixel differencing detect all changes between imagery and are thus not well suited for detecting target-specific changes, such as riparian zones within a selected watershed. Thus, targets must first be extracted from both sets of imagery before target changes can be detected. Previous research by others to accelerate the target recognition process has generally resulted in slow, complex, and task-specific programs that are unable to adapt to different situations, such as changing target features, geographic areas, seasons, image data types, or image spatial resolutions. This article discusses a new software product, Feature Analyst (www.featureanalyst.com), that succeeds in automating the change detection process.

Background

Features extracted from an image populate a GIS database and support decision-makers for a wide variety of applications such as land-use planning, disaster and emergency services, telecommunications, etc. Image classifiers can also be used to extract from imagery some types of specific objects or targets, such as land-cover types using multispectral imagery (MSI). The real world task of feature extraction, however, it is impossible to extract many features using only spectral information. For example one cannot distinguish between asphalt roads and asphalt parking lots without using contextual information

provided by spatial signatures. The classifier must not look only at the spectral value of a pixel but also look at surrounding pixels to infer the notion of spatial perspective.

Besides manual classification and traditional image processing techniques, an alternate and more recent approach is to model the feature extraction process using statistical and machine learning techniques (Maloof et al. 1998; McKeown 1996). The idea behind this approach is that, with a sample of extracted features from the image, a learning algorithm automatically develops a model that correlates known data (such as pixel values from images, terrain data, vector overlays, grids etc.) with targeted features. The learned model then automatically classifies and extracts the remaining features in the imagery. Traditional supervised classification methods have predominately used basic statistical methods, such as Maximum Likelihood. These methods require a priori statistical assumptions and often fail on small-feature capture because of their inability to (a) classify disjunctive concepts, (b) take into account spatial context, and (c) remove clutter.

This paper examines a new approach to change detection, Feature Analyst, by Visual Learning Systems, Inc. Feature Analyst makes inductive learning the focal point of its extraction process. Feature Analyst provides (a) a simple interface and workflow process, (b) ability to take into account spatial context (contextual classification), (c) the ability to mitigate clutter, and (d) the ability to learn disjunctive concepts. Feature Analyst is available as an extension to ArcGIS and ERDAS IMAGINE. Feature Analyst works by having an analyst provide sample changes of targets in an image set, then it learns from these examples and automatically detects the remaining changes in the image set.

Problem representation is of the utmost importance for inductive learning. With feature extraction, the difficulty is including enough spatial information without overwhelming the learner. Figures 1-3 from Opitz, 2002 show the value of using spatial content in feature extraction. Figure 1 shows an image where we want to extract white lines on airport runways. Figure 2 demonstrates the best one can do using only spectral information. Since all materials with similar reflectance as the white lines are extracted, there is too much clutter. Results using Feature Analyst using a "square 7x7" input window is shown in Figure 3. Only thin white lines surrounded by pavement and/or grass are extracted. Opitz, 2002, showed that using a proper spatial context when extracting NIMA's Foundation Feature Classes resulted in features that reduced the error rate from traditional supervised classification by over 50%. Feature Analyst showed a labor savings of over 165 times as compared to heads-up digitizing, without sacrificing accuracy.

Figure 1: Sample image where we want the white lines on the airport runway.

Figure 2: Supervised classification with no spatial context.

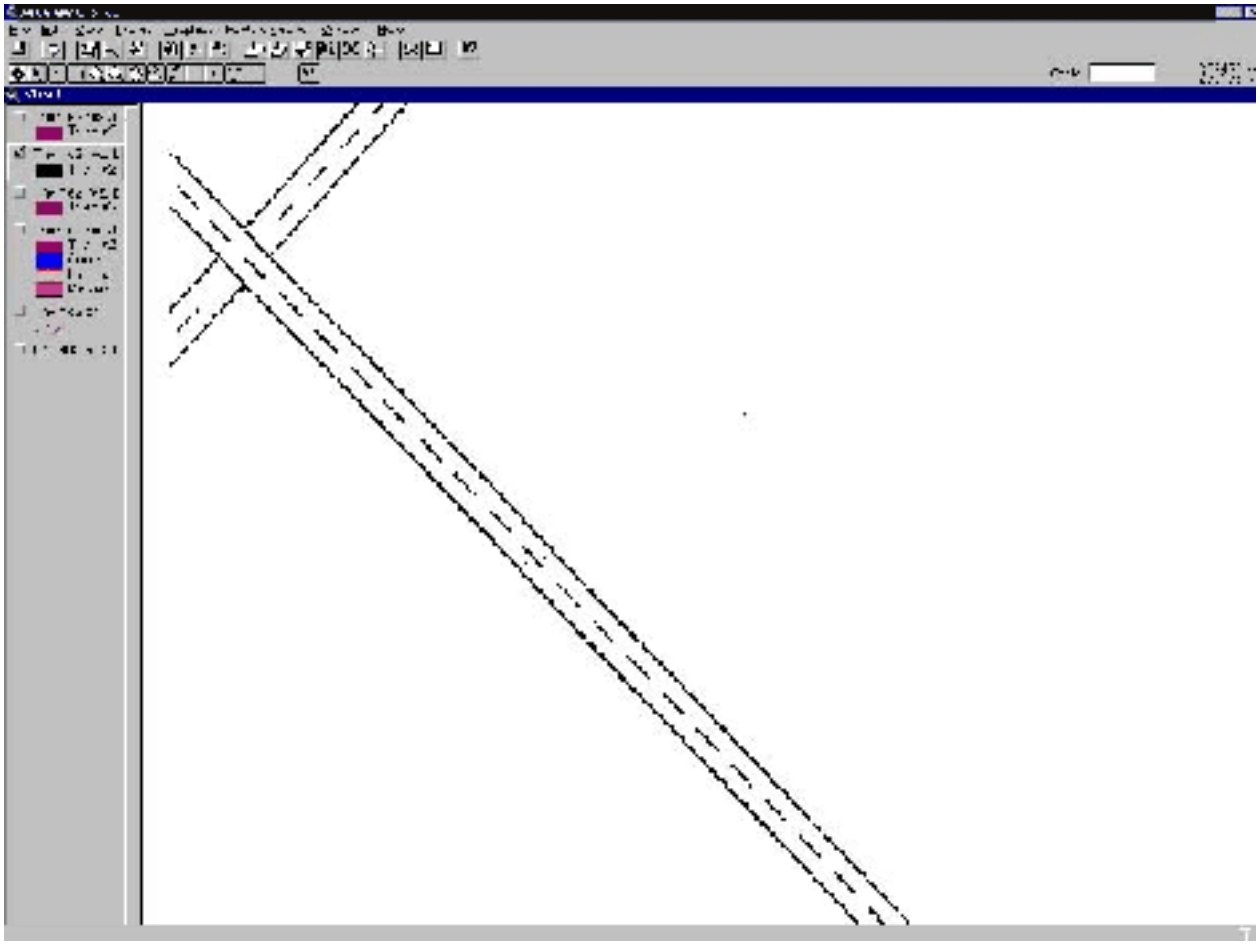

Figure 3: Feature Analyst classification with spatial context.

Results

Figures 4-9 illustrate the difficulties of current techniques, then shows the solution of the Feature Analyst. Figures 4 and 5 show a pre-date and a post-date image of a runway painting project. In this experiment, we are only concerned with the newly painted thin lines at the edge and middle of the runway; we do not want the newly painted path at the upper right corner of the image, nor do we want the thin lines painted before the pre-date image. A successful technique must (a) take into account spatial information (e.g., recognize a linear white feature with pavement or grass on both sides), and (b) reduce unwanted clutter that devastate most change-detection attempts. Figure 6 shows the result of excluding spatial information (i.e., just use the center pixel in the window); note that all pavement that became white in the post-date image is extracted. Figure 7 shows the results after extracting white lines from both images, then differencing the two resulting vectors. It is widely documented that such differencing does not work because the same object is rarely extracted 100% the same in both images (especially with high resolution imagery), and thus outlines of objects nearly always appear. Figure 8 shows the results of the Feature Analyst after the first pass of learning, and Figure 9 shows the results after the second pass of learning with clutter removed. Note the second pass of learning was able to learn this one type of change. Thus, Feature Analyst's spatial representation of inputs, learning methods, and hierarchical clutter removal allow feature-specific change detection, something heretofore unachievable

with current commercial approaches.

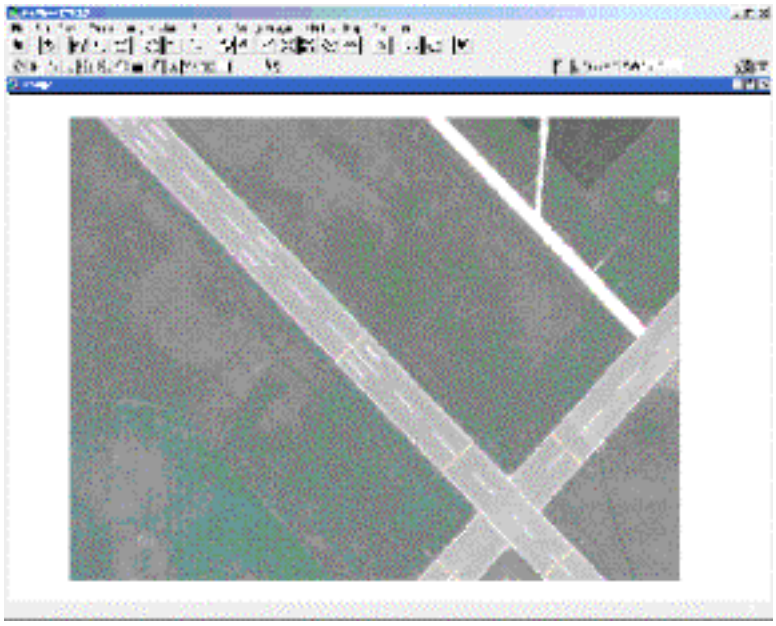

Figure 4: The pre-date image with partially painted lines.

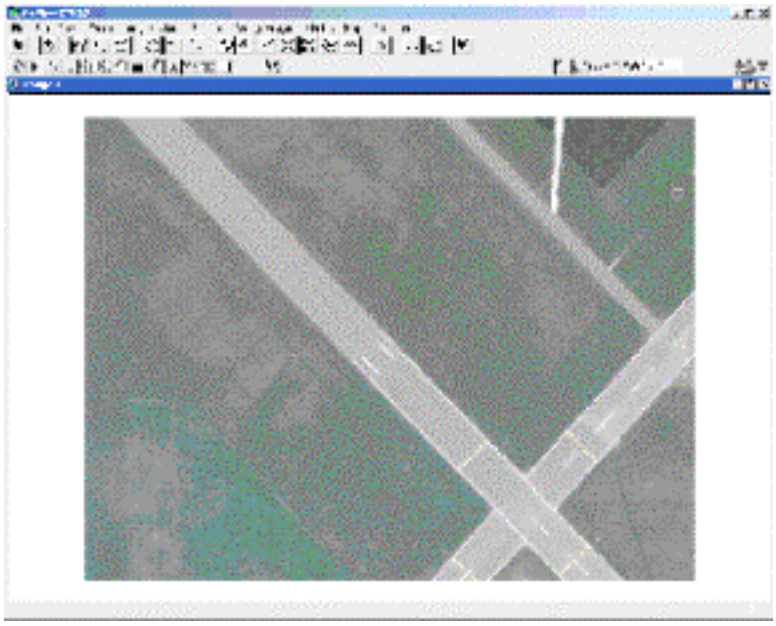

Figure 5: The post-date image after lines on the runway were fully painted.

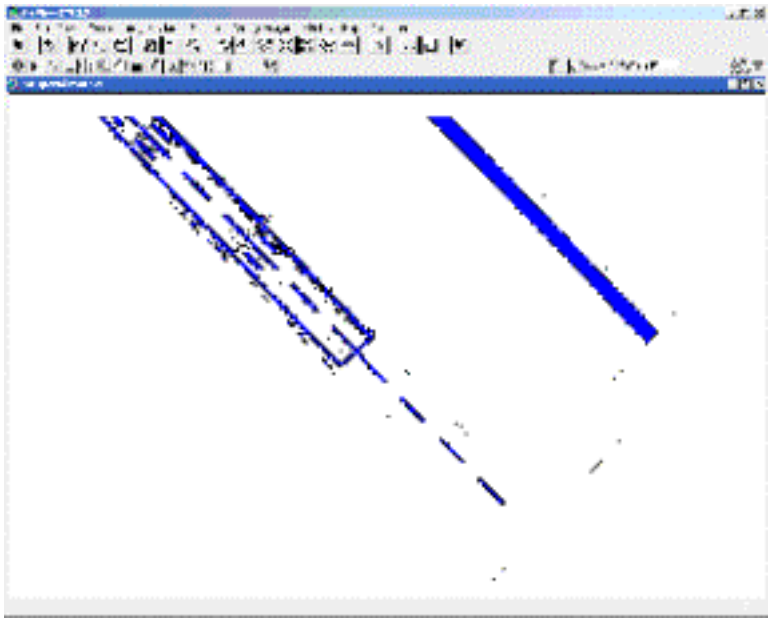

Figure 6: Results using no spatial context.

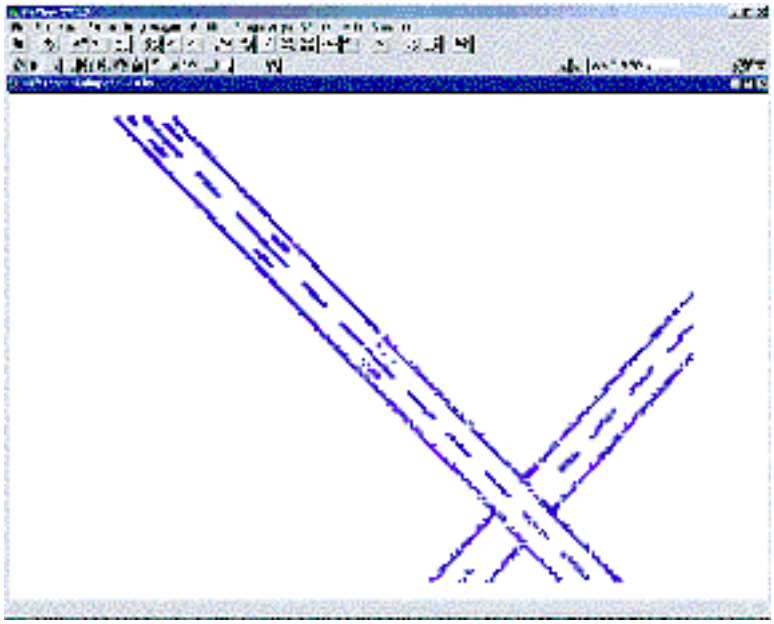

Figure 7: Results after differencing the shape files of extracted runway lines.

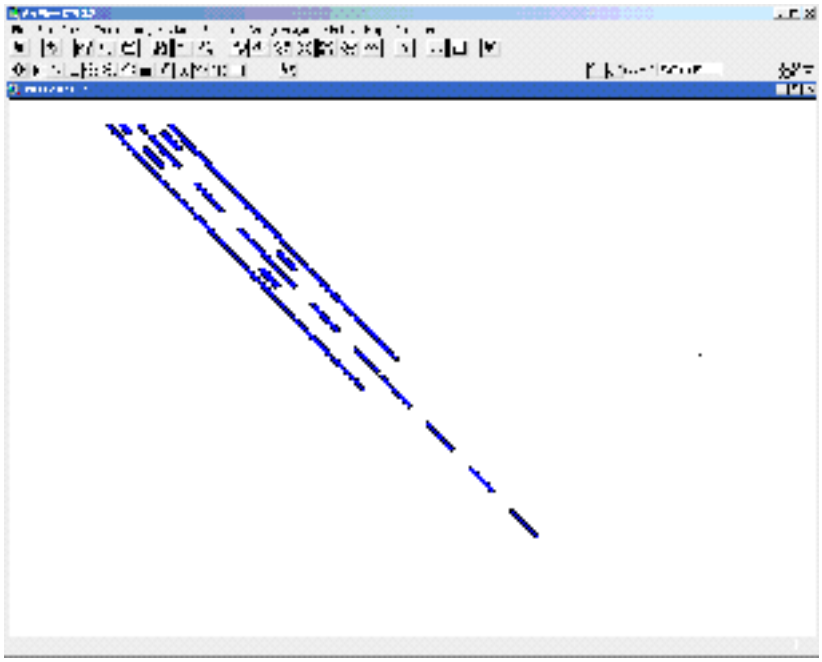

Figure 8: Results after one pass of the Feature Analyst.

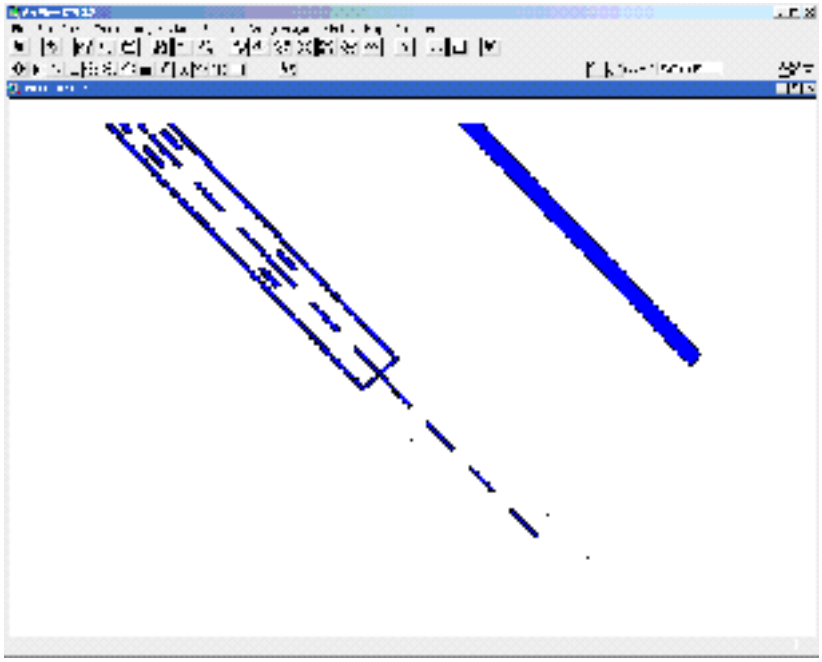

Figure 9: Results after two passes of the Feature Analyst (99.7% correct).

Conclusions

Feature Analyst is an exciting new product that is able to detect feature specific changes in imagery over time. Proper spatial context can automate the change detection process and result in significant labor savings. Feature Analyst, with its easy-to-use interface, promises to become the way analysts detect changes is their GIS database.

Acknowledgements

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