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Feature Extraction & Classification

Solutions Paper

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Feature Extraction & Classification

Introduction

Any given remote sensing image can be decomposed into several features. The term ‘feature’ refers to remote sensing scene objects (e.g. vegetation types, urban materials, etc) with similar characteristics (whether they are spectral, spatial or otherwise). Therefore, the main objective of a feature extraction technique is to accurately retrieve these features. The term “Feature Extraction” can thus be taken to encompass a very broad range of techniques and processes, ranging from simple ordinal / interval measurements derived from individual bands (such as thermal temperature) to the generation, update and maintenance of discrete feature objects (such as buildings or roads).

The definition can also be taken to encompass manual and semi-automated (or assisted) vector feature capture – however “Feature Collection” is the topic of a separate White Paper not discussed further here. Similarly, derivation of height information from stereo or interferometric techniques could be considered feature extraction but is discussed elsewhere.

What follows is a discussion of the range and applicability of feature extraction techniques available within Leica Geosystems Geospatial Imaging’s suite of remote sensing software applications.

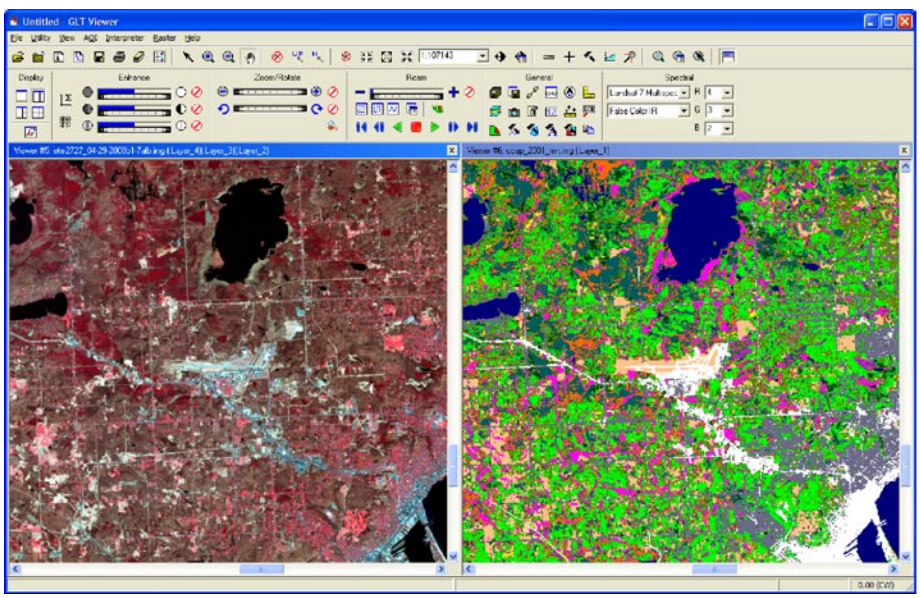

Figure 1: Unsupervised Classification of the Landsat data on the left and manual cleanup produced the land cover classification shown on the right.

Derived Information

To many analysts, even ordinal or interval measurements derived directly from the DN values of imagery represent feature extraction. ERDAS IMAGINE® and ERDAS ERM Pro provide numerous techniques of this nature, including (but not limited to):

The direct calibration of the DN values of the thermal bands of satellite and airborne sensors to derive products such as Sea Surface Temperature (SST) and Mean Monthly SST.

One of the most widely known derived feature types is vegetation health through the Normalized Difference Vegetation Index (NDVI), where the red and near-infrared (NIR) wavelength bands are ratioed to produce a continuous interval measurement taken to represent the proportion of vegetation / biomass in each pixel or the health/vigor of a particular vegetation type. Other types of features can also be derived using indices, such as clay and mineral composition.

Principal Component Analysis (PCA - Jia and Richards, 1999) and Minimum Noise Fraction (MNF - Green et al., 1988) are two widely employed feature extraction techniques in remote sensing. These techniques aim to de-correlate the spectral bands to recover the original features. In other words, these techniques perform linear transformation of the spectral bands such that the resulting components are uncorrelated. With these techniques, the "feature" being extracted is more abstract – for example, the first principal component is generally held to represent the high frequency information present in the scene, rather than representing a specific land use or cover type.

The Independent Component Analysis (ICA) based feature extraction technique performs a linear transformation to obtain the independent components (ICs). A direct implication of this is that each component will contain information corresponding to a specific feature.

As well as being used as stand-alone feature extraction techniques, many are also used as inputs for the techniques discussed below. This can take one of two forms – for high dimensionality data (hyperspectral imagery, etc), the techniques can minimize the noise and the dimensionality of the data (in order to promote more efficient and accurate processing), whereas for low dimensionality data (grayscale data, RGB imagery, etc.) they can be used to derive additional layers (NDVI, texture measures, higher-order Principal Components, etc). The additional layers are then input with the source image in a classification / feature extraction process to provide output that is more accurate.

Other techniques aimed at deriving information from raster data can also be thought of as feature extraction. For example, Intervisibility/Line Of Site (LOS) calculations from Digital Elevation Models (DEMs) represent the extraction of a "what can I see" feature.

Similarly, tools like the IMAGINE Modeler Maker enable customers to develop custom techniques for feature extraction in the broader context of geospatial analysis, such as "where is the best location for my factory" or "where are the locations of significant change in land cover."

Such derived feature information are also candidates for input to some of the more advanced feature extraction techniques discussed below, such as providing ancillary information layers to object-based feature extraction approaches.

Supervised Classification

Multispectral classification is the process of sorting pixels into a finite number of individual classes, or categories of data, based on their data file values. If a pixel satisfies a certain set of criteria, the pixel is assigned to the class that corresponds to those criteria.

Depending on the type of information you want to extract from the original data, classes may be associated with known features on the ground or may simply represent areas that look different to the computer. An example of a classified image is a land cover map, showing vegetation, bare land, pasture, urban, etc.

To classify, statistics are derived from the spectral characteristics of all pixels in an image. Then, the pixels are sorted based on mathematical criteria. The classification process breaks down into two parts: training and classifying (using a decision rule).

First, the computer system must be trained to recognize patterns in the data. Training is the process of defining the criteria by which these patterns are recognized. Training can be performed with either a supervised or an unsupervised method, as explained below.

Supervised training is closely controlled by the analyst. In this process, you select pixels that represent patterns or land cover features that you recognize, or that you can identify with help from other sources, such as aerial photos, ground truth data or maps. Knowledge of the data, and of the classes desired, is therefore required before classification. By identifying these patterns, you can instruct the computer system to identify pixels with similar characteristics. The pixels identified by the training samples are analyzed statistically to form what are referred to as signatures.

After the signatures are defined, the pixels of the image are sorted into classes based on the signatures by use of a classification decision rule. The decision rule is a mathematical algorithm that, using data contained in the signature, performs the actual sorting of pixels into distinct class values. If the classification is accurate, the resulting classes represent the categories within the data that you originally identified with the training samples.

Supervised Classification can be used as a term to refer to a wide variety of feature extraction approaches; however, it is traditionally used to identify the use of specific decision rules such as Maximum Likelihood, Minimum Distance and Mahalonobis Distance.

Unsupervised Classification

Unsupervised training is more computer-automated. It enables you to specify some parameters that the computer uses to uncover statistical patterns that are inherent in the data. These patterns do not necessarily correspond to directly meaningful characteristics of the scene, such as contiguous, easily recognized areas of a particular soil type or land use. The patterns are simply clusters of pixels with similar spectral characteristics. In some cases, it may be more important to identify groups of pixels with similar spectral characteristics than it is to sort pixels into recognizable categories.

Unsupervised training is dependent upon the data itself for the definition of classes. This method is usually used when less is known about the data before classification. It is then the analyst's responsibility, after classification, to attach meaning to the resulting classes. Unsupervised classification is useful only if the classes can be appropriately interpreted. ERDAS IMAGINE provides several tools to assist in this process, the most advanced being the Grouping Tool.

The Unsupervised approach does have its advantages. Since there is no reliance on user-provided training samples (which might not represent “pure” examples of the class / feature desired and which would therefore bias the results), the algorithmic grouping of pixels is often more likely to produce statistically valid results. Consequently, many users of remotely sensed data have switched to allowing software to produce homogenous groupings via unsupervised classification techniques and then use the locations of training data to help label the groups.

The classic Supervised and Unsupervised Classification techniques (as well as hybrid approaches utilizing both techniques and fuzzy classification) have been used for decades with great success on medium to lower resolution imagery (imagery with pixel sizes of 5m or larger), however one of their significant disadvantages is that their statistical assumptions generally preclude their application to high resolution imagery. They are also hampered by the necessity for multiple bands to increase the accuracy of the classification. The trend toward higher resolution sensors means that the number of available bands to work with is generally reduced.

Hyperspectral

Optical sensors can be broken into three basic classes: panchromatic, multispectral and hyperspectral. Multispectral sensors typically collect a few (3-25), wide (100-200 nm), and possibly, noncontiguous spectral bands. Conversely, Hyperspectral sensors typically collect hundreds of narrow (5-20 nm) contiguous bands.

The name, hyperspectral, implies that the spectral sampling exceeds the spectral detail of the target (i.e., the individual peaks, troughs and shoulders of the spectrum are resolvable). Given finite data transmission and/or handling capability, an operational satellite system must make a trade-off between spatial and spectral resolution. This same trade-off exists for the analyst or data processing facility. Thus, in general, as the number of bands increases there must be a corresponding decrease in spatial resolution. This means that most pixels are mixed pixels and most targets (features) are subpixel in size. It is, therefore, necessary to have specialized algorithms which leverage the spectral resolution of the sensor to clarify subpixel targets or components.

Hyperspectral classification techniques constitute algorithms (such as Orthogonal Subspace Projection, Constrained Energy Minimization, Spectral Correlation Mapper, Spectral Angle Mapper, etc.) tailored to efficiently extract features from imagery with a large dimensionality (number of bands) and where the feature generally does not represent the “primary” constituent of the sensors instantaneous field of view. This is also often performed by comparison to laboratory derived material (feature) spectra as opposed to imagery-derived training samples, which also necessitate a suite of pre-processing and analysis steps tailored to hyperspectral imagery.

Subpixel Classification

IMAGINE Subpixel Classifier™ is a supervised, non-parametric spectral classifier that performs subpixel detection and quantification of a specified material of interest (MOI). The process allows you to develop material signatures and apply them to classify image pixels. It reports the pixel fraction occupied by the material of interest and may be used for materials covering as low as 20% of a pixel.

Additionally, its unique image normalization process allows you to apply signatures developed in one scene to other scenes from the same sensor.

Because it addresses the “mixed pixel problem,” IMAGINE Subpixel Classifier successfully identifies a specific material when other materials are also present in a pixel. It discriminates between spectrally similar materials, such as individual plant species, specific water types or distinctive building materials. Additionally, it allows you to develop spectral signatures that are scene-to-scene transferable.

IMAGINE Subpixel Classifier enables you to:

- Classify objects smaller than the spatial resolution of the sensor
- Discriminate specific materials within mixed pixels
- Detect materials that occupy from 100% to as little as 20% of a pixel
- Report the fraction of material present in each pixel classified
- Develop signatures portable from one scene to another
- Normalize imagery for atmospheric effects
- Search wide-area images quickly to detect small or large features mixed with other materials

The primary difference between IMAGINE Subpixel Classifier and traditional classifiers is the way in which it derives a signature from the training set and then applies it during classification. Traditional classifiers typically form a signature by averaging the spectra of all training set pixels for a given feature. The resulting signature contains the contributions of all materials present in the training set pixels. This signature is then matched against whole-pixel spectra found in the image data. In contrast, IMAGINE Subpixel Classifier derives a signature for the spectral component that is common to the training set pixels following background removal. This is normally a pure spectrum of the material of interest. Since materials can vary slightly in their spectral appearance, IMAGINE Subpixel Classifier accommodates this variability within the signature. The IMAGINE Subpixel Classifier signature is therefore “purer” for a specific material and can more accurately detect the MOI. During classification, the process subtracts representative background spectra to find the best fractional match between the pure signature spectrum and candidate residual spectra.

IMAGINE Subpixel Classifier and traditional classifiers perform best under different conditions. IMAGINE Subpixel Classifier should work better to discriminate different species of vegetation, distinctive building materials or specific types of rock or soil. You would use it to find a specific material even when it covers less than a pixel. You may prefer a traditional classifier when the MOI is composed of a spectrally varied range of materials that must be included as a single classification unit. For example, a forest that contains a large number of spectrally distinct materials (heterogeneous canopy) and spans multiple pixels in size may be classified better using a minimum distance classifier. IMAGINE Subpixel Classifier can compliment a traditional classifier by identifying subpixel occurrences of specific species of vegetation within that forest. When deciding to use IMAGINE Subpixel Classifier, recall that it identifies a single material, the MOI, whereas a traditional classifier will classify many materials or features occurring with a scene. The Subpixel Classification process can thus be considered a feature extraction process rather than a “wall to wall” classification process.

In principle, IMAGINE Subpixel Classifier can be used to map any material that has a distinct spectral signature relative to other materials in a scene. IMAGINE Subpixel Classifier has been most thoroughly evaluated for vegetation classification applications in forestry, agriculture and wetland inventory, as well as for man-made objects, such as construction materials. IMAGINE Subpixel Classifier has also been used in defining roads and waterways.

Classification accuracy depends on many factors. Some of the most important are:

1) Number of spectral bands in the imagery. Discrimination capability increases with the number of bands. Smaller pixel fractions can be detected with more bands. The 20% threshold used by the software is based on 6-band data.
2) Target/background contrast.
3) Signature quality. Ground truth information helps in developing and assessing signature quality.
4) Image quality, including band-to-band registration, calibration and resampling (nearest neighbor preferred).

Two projects involving subpixel classification of wetland tree species (Cypress and Tupelo) and of an invasive forest tree species (Loblolly Pine) included extensive field checking for classification refinement and accuracy assessment. The classification accuracy for these materials was 85-95%. Classification of pixels outside the training set area was greatly improved by IMAGINE Subpixel Classifier in comparison to traditional classifiers.

Figure 2: Test using panels highlights the greater accuracy of detection provided by a subpixel classifier over a traditional classifier, especially where panels were smaller in size than the pixel resolution.

In a separate quantitative evaluation study designed to assess the accuracy of IMAGINE Subpixel Classifier, hundreds of man-made panels of various known sizes were deployed and imaged. The approximate amount of panel in each pixel was measured. When compared to the Material Pixel Fraction (the amount of material in each pixel) reported by IMAGINE Subpixel Classifier, a high correlation was measured. IMAGINE Subpixel Classifier outperformed a maximum likelihood classifier in detecting these panels. It detected 190% more of the pixels containing panels, with a lower error rate, and reported the amount of panel in each pixel classified.

IMAGINE Subpixel Classifier works on any multispectral data source, including airborne or satellite, with three or more spatially registered bands. The data must be in either 8-bit or 16-bit format. Landsat Thematic Mapper (TM), SPOT XS and IKONOS multispectral imagery have been most widely used because of data availability. It will also work with data from other high resolution commercial sensors such as Quickbird, FORMOSAT-2, airborne sources and OrbView-3.

IMAGINE Subpixel Classifier will also work with most hyperspectral data sources.

Expert Knowledge-Based Classification

One of the major disadvantages to most of the techniques discussed above is that they are all per-pixel classifiers. Each pixel is treated in isolation when using the technique to determine which feature or class to assign it to – there is no provision to use additional cues such as context, shape and proximity, cues which the human visual interpretation system takes for granted when interpreting what it sees. One of the first commercially available attempts to overcome these limitations was the IMAGINE Expert Classifier.

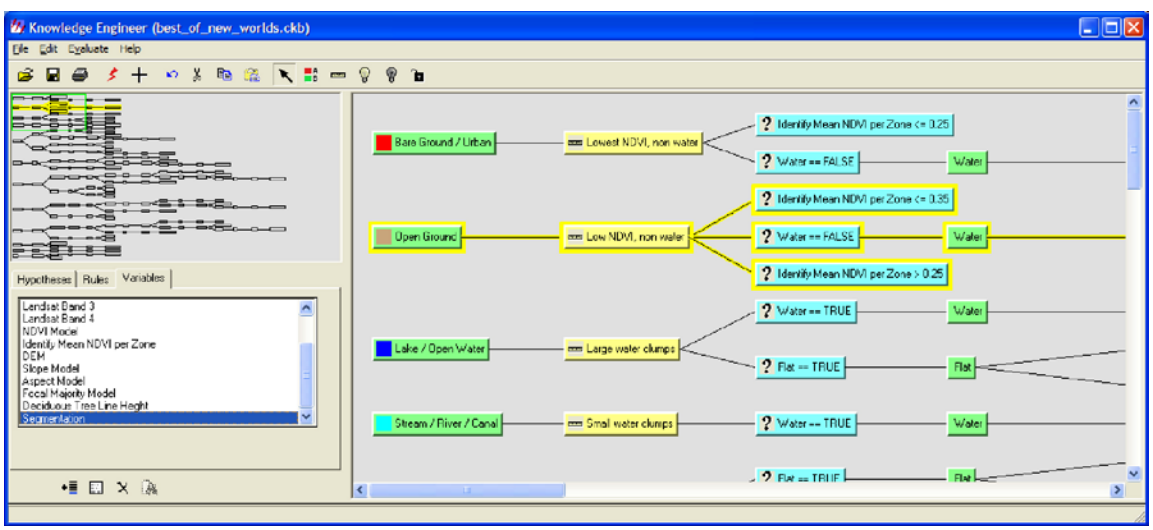

Figure 3: The Knowledge Engineer showing a decision tree leading to land use classes.

The expert classification software provides a rules-based approach to multispectral image classification, post-classification refinement and GIS modeling. In essence, an expert classification system is a hierarchy of rules, or a decision tree that describes the conditions for when a set of low level constituent information gets abstracted into a set of high level informational classes. The constituent information consists of user-defined variables and includes raster imagery, vector layers, spatial models, external programs and simple scalars.

A rule is a conditional statement, or list of conditional statements, about the variable's data values and/or attributes that determine an informational component or hypotheses. Multiple rules and hypotheses can be linked together into a hierarchy that ultimately describes a final set of target informational classes or terminal hypotheses. Confidence values associated with each condition are also combined to provide a confidence image corresponding to the final output classified image.

While the Expert Classification approach does enable ancillary data layers to be taken into consideration, it is still not truly an object based means of image classification (rules are still evaluated on a pixel by pixel basis). Additionally, it is extremely user-intensive to build the models – an expert is required in the morphology of the features to be extracted, which also then need to be turned into graphical models and programs that feed complex rules, all of which need building up from the components available. Even once a knowledge base has been constructed it may not be easily transportable to other images (different locations, dates, etc).

Image Segmentation

Segmentation means the grouping of neighboring pixels into regions (or segments) based on similarity criteria (digital number, texture). Image objects in remotely sensed imagery are often homogenous and can be delineated by segmentation. Thus, the number of elements, as a basis for a following image classification, is enormously reduced if the image is first segmented. The quality of subsequent classification is directly affected by segmentation quality.

Ultimately, Image Segmentation is also another form of unsupervised image classification, or feature extraction. However, it has several advantages over the classic multispectral image classification techniques, the key discriminators being the ability to apply it to panchromatic data and also to high resolution data.

However, Image Segmentation is also similar to the unsupervised approach of image classification in that it is an automated segregation of the image into groups of pixels with like characteristics without any attempt to assign class names or labels to the groups. It suffers from an additional drawback in that there is generally no attempt made at the point of producing the segmentation to use the segment characteristics to identify similar segments. With Unsupervised Classification you may have widely separated, distinct groups of pixels, but their statistical similarity means they are assigned to the same class (even though you do not yet know what feature type that class is), whereas with Image Segmentation, each segment is simply uniquely identified. Statistical measures can usually be recorded per segment to help with post processing.

Consequently, in order to label the segments with a feature type / land cover, the technique must be combined with some other form of classification, such as Expert Knowledge-Based Classification or as part of the Feature Extraction workflow provided by IMAGINE Objective.

Object-based Feature Extraction and Classification

Globally, GIS departments and mapping institutions invest considerable revenue into creating and, perhaps more importantly, maintaining their geospatial databases. As the Earth is constantly changing, even the most precise base mapping must be updated or replaced regularly. Traditionally, the capture and update of geospatial information has been done through labor and cost intensive manual digitization (for example from aerial photographs) and post-production surveying.

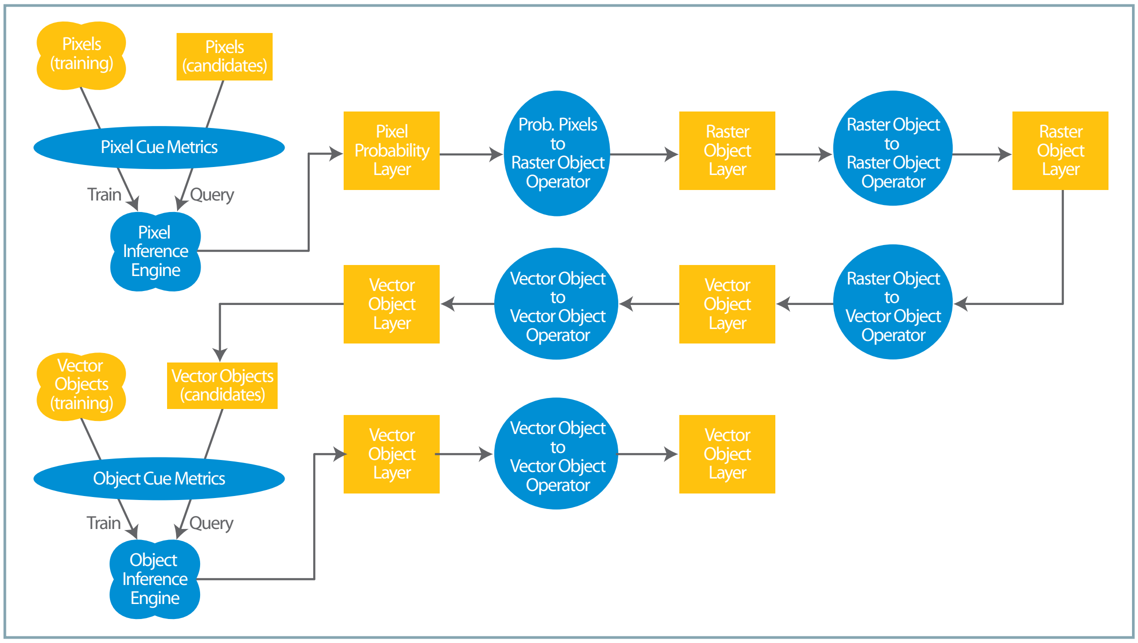

Figure 4: The basic structure of a feature model showing the linear manner in which the data is analyzed. Operators are designed as plug-ins so that more can be easily added as required for specific feature extraction scenarios.

Since then, various attempts have been made to help automate these workflows by analyzing remotely sensed imagery. Remotely sensed imagery, whether airborne or satellite based, provides a rich source of timely information if it can be easily exploited into useable information. These attempts at automation have often resulted in limited success, especially as the resolution of imagery and the intended mapping scale increases. With recent innovations in geospatial technology, we are now at a place where workflows can be successfully automated.

When Landsat was launched more than 30 years ago, it was heralded as a new age for automating mapping of the Earth. However, the imagery, and therefore the geospatial data dervied from it, was of relatively coarse resoution, and thereby became limited to smaller scale mapping applications. Its analysis was also restricted to “remote sensing experts.” Equally, the traditional supervised and unsupervised classification techniques developed to extract information from these types of imagery were limited to coarser resolutions. Today’s sources for higher resolution imagery (primarilly meaning 1m or smaller pixel sizes, such as that produced by the IKONOS, QuickBird, and WorldView satelittes or by airborne sensors) do not suffer from the “mixed pixel” phenomenon seen with lower resolution imagery, and, therefore the statistical assumptions which must be met for the traditional supervised and unsupervised classification techniques do not hold. Thus, more advanced techniques are required to analyze the high resolution imagery required to create and maintain large scale mapping and geospatial databases. The best techniques for addressing this problem analyze the imagery on an object, as opposed to pixel, basis.

Figure 5: The IMAGINE Objective user interface showing a feature model designed to extract the locations of building footprints in a GIS-ready format to minimize manual post-processing and editing.

IMAGINE Objective provides object based multi-scale image classification and feature extraction capabilities to reliably build and maintain accurate geospatial content. With IMAGINE Objective, imagery and geospatial data of all kinds can be analyzed to produce GIS-ready mapping.

IMAGINE Objective includes an innovative set of tools for feature extraction, update and change detection, enabling geospatial data layers to be created and maintained through the use of remotely sensed imagery. This technology crosses the boundary of traditional image processing with computer vision through the use of pixel level and true object processing, ultimately emulating the human visual system of image interpretation.

Catering to both experts and novices alike, IMAGINE Objective contains a wide variety of powerful tools. For remote sensing and domain experts, IMAGINE Objective includes a desktop authoring system for building and executing feature-specific (buildings, roads, etc) and/or landcover (e.g., vegetation type) processing methodologies. Other users may adjust and apply existing examples of such methodologies to their own data. The user interface enables the expert to set up feature models required to extract specific feature types from specific types of imagery. For example, road centerlines from 60cm Color-Infrared (CIR) satellite imagery require a specific feature model based around different image-based cues. Building footprints from six inch true color aerial photography and LIDAR surface models require a different feature model. For those familiar with existing ERDAS IMAGINE® capabilities, an analogy can be drawn with Model Maker, with its ability to enable experienced users to graphically build their own spatial models using the primitive building blocks provided in the interface. The less experienced user can simply use built-in example Feature Models or those built by experts, applying them as-is or modifying through the user interface.

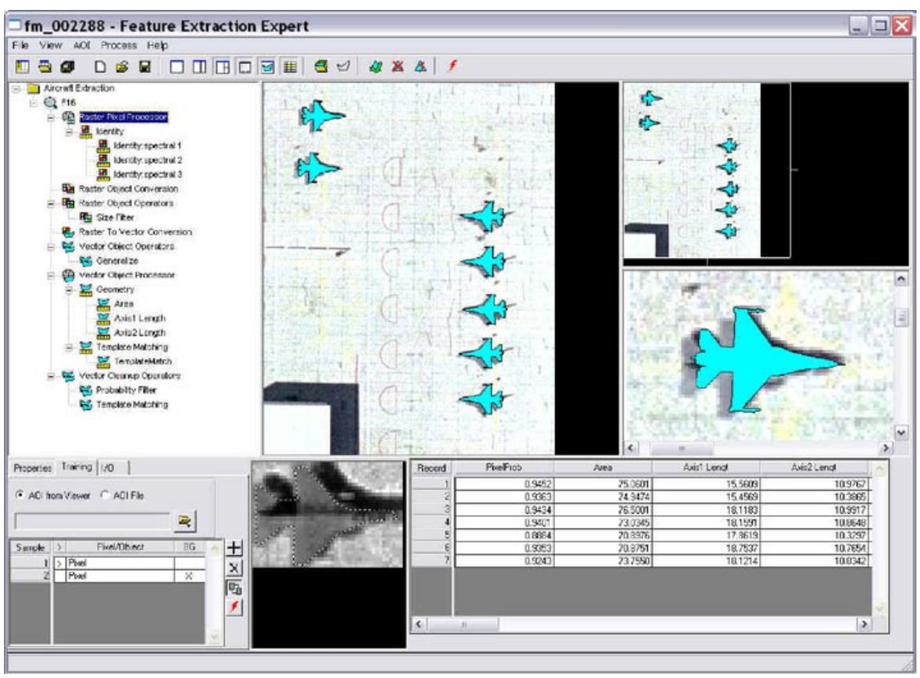

Figure 6: The IMAGINE Objective user interface showing a feature model designed to identify locations of a particular aircraft type.

While similar to the IMAGINE Expert Classifier approach, the construction and use of feature models within IMAGINE Objective is simpler and more powerful. Constructing a feature model is more linear and intuitive to the expert building the model. In addition, the support for supervised training and evidential learning of the classifier itself means that the feature models are more transportable to other images once built.

ERDAS' patent pending approach uses a unique combination of artificial intelligence, computer vision, and traditional image processing and remote sensing technologies. As a result, the algorithms perform not only raster contouring (stair-stepped results), but also incorporate object and vector level processing to yield a spatially matched, precise shape for each feature.

Consequently, the output generated from the product will be GIS-ready, such as smooth roads and squared-up buildings. Therefore, the output can be directly merged into a GIS with no other post-processing, and will accurately reflect the image content. Outputs include clean vector outlines and auto-attribution of polygons with probability measures enabling querying of dubious results for quality control purposes.

IMAGINE Objective comes with several pre-defined example Feature Models for classifying imagery and extracting features. These feature models can be quickly adjusted to work on your own data.

Users may also build their own Feature Models for solving other problem scenarios not yet covered by the examples.

The object-based feature extraction methodology highlighted by IMAGINE Objective has significant advantages over older techniques, including:

- Offers open, modifiable and extensible feature models. This flexibility means that the classifier can be fine-tuned to the specific circumstances of the imagery being analyzed if initial results are not adequate

- True object-oriented approach means that in addition to spectral properties being utilized, the spatial components are also measurable and available to the processing engine

- Caters to discrete feature extraction (e.g. where are the buildings) and multi-class extractions (wall to wall classification), providing a flexible tool for a variety of problem scenarios

- Provides discrete feature extraction, where clean-up operators can be included in the feature model to produce output suitable for merging into a GIS with minimal post-processing (squared-up buildings, smooth gap-less roads, aircraft outlines, etc)

- Integrates with ERDAS IMAGINE, providing a full suite of vector editing tools for further clean-up and editing. This integration provides an end-to-end feature extraction process within one integrated package. Other workflows often require steps to be performed in different software packages, with the inherent capability for loosing information and efficiency

- Utilizes ancillary layers (data fusion) – e.g. slope, aspect, LIDAR, texture, along with the capability inherent with an object based approach to employ shape metrics, proximity, association, leading to increased feature extraction accuracy

- Leverages holdings of all remotely sensed imagery, including panchromatic, multispectral, hyperspectral, SAR, LIDAR, etc.

- Extracts features and classes which are attributed based on the measures used to identify them, including a final probability of being that class, enabling quicker validation of final results and analysis of problem areas

- Provides the ability to prototype and test a new feature model on user-selected view windows (even if the training evidence lies outside the area to be processed) for rapid fine-tuning and applying the finished feature model to the whole data set (or to different data sets)

- Deploys floating licenses as standard, ensuring that maximum usage of the software can be made across an institution's network

Feature Analyst® for ERDAS IMAGINE® and ArcGIS®

Feature Analyst is a 2D automated feature extraction package that is available as an add-on for any level of ERDAS IMAGINE® or ArcGIS®. The software is wizard based allowing the user to make a simple selection on the type of features extracted. The user must then set up a number of training samples and iterate through a process of training the software on correct and incorrect hits before a final feature layer can be extracted. Clean-up tools are provided within the software for improving the automated results. The platforms, ERDAS IMAGINE and ArcGIS, also have a number of tools for manually improving results. Its ability to extract pervious/impervious maps from high resolution imagery has been a strong selling point for the product in state/local government mapping. In the defense market, its quick and easy wizard setup has made it popular for high-level use.

There have been two distinct feature extraction solutions to emerge in the market; the wizard based approaches and more user defined approaches. Feature Analyst follows the first path with its "point and click" black box approach to extraction. Conversely, a package like IMAGINE Objective relies upon a combination of expert knowledge and inferential learning and that requirement for expert knowledge (i.e. what cues are appropriate to measure in an image to help discriminate a particular feature type) puts it into the path of a more user defined, open approach. The two approaches are equally valid and useful–the one most appropriate to solving a specific problem will largely depend on the data being use and the type of feature of interest.

LIDAR Analyst™ for ERDAS IMAGINE® and ArcGIS®

LIDAR Analyst for ERDAS IMAGINE and ArcGIS is an automated feature extraction package for bare earth generation, building footprint, single tree and forested areas extraction from LIDAR data.

Area Frame Sampling

It is worth mentioning this technique in a discussion of feature extraction and image classification as it serves a very useful purpose even though it does not, strictly speaking, result in a mapping of features. Instead, area frame sampling provides information extraction based on feature extraction samples and statistical estimation to a broader area.

For example, if you needed to quantify the amount of land that is covered by parking lots on a university campus, how would you go about accomplishing this? You could survey parking lots, or you could get aerial photography of the campus and digitize these using the feature extraction techniques mentioned. However, what if you wanted to analyze the amount of land covered by forests in an entire county, or the amount of arable land planted with grain in a continent? The cost of collecting ground truth data from the entire county or of digitizing a continent would prohibit an accurate assessment.

The process of Area Frame Sampling provides an answer to these types of problems. Area Frame Sampling is a statistical methodology that enables the accurate survey of a MOI in the study area. As the name suggests, Area Frame Sampling uses a frame to define the study area and the analysis of representative samples from within that frame to estimate the proportion of the MOI in the frame.

While collecting ground truth from an entire county or digitizing a continent might not be feasible, it would certainly make sense to use ground truth and imagery interpretation to calculate the amount of the MOI in these representative samples.

The use of Area Frame Sampling and remote sensing can assist the surveyor in achieving the most accurate estimate for the least cost. Remote Sensing provides the analyst with a synoptic view of the entire Frame. The classification methods discussed provide methods of "stratification," or creating smaller homogenous units that represent the entire Frame. This stratification reduces the number of samples that are allocated to provide an accurate result. High resolution aerial photography can be used in the labeling of the areas containing the MOI in the representative samples, thereby limiting the amount of ground truth data that needs to be collected. The areas of the feature of interest in the high-res samples are then extrapolated up to the broader area stratification to provide a statistical estimate of the occurrence of the MOI across the broad area. While you may not know exactly where the MOI occurs, you do know, with a stated level of accuracy, how much of the MOI is present in the broader area.

This technique provides for a very cost effective approach to information extraction by minimizing the extent to which high resolution imagery (and associated ground truth) must be acquired.

Feedback

If you have any questions or comments regarding the content of this paper please contact:

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