

# Automating Feature Extraction with IMAGINE Objective

**White Paper**



## Automating Feature Extraction with IMAGINE Objective

IMAGINE Objective provides tools for feature extraction, update and change detection, enabling geospatial data layers to be created and maintained using remotely sensed imagery. IMAGINE Objective combines inferential learning with expert knowledge in a true object-oriented feature extraction environment. The object-oriented approach enables the software to emulate human visual processing by analyzing the data not just on a pixel by pixel basis but also by looking at object-based measures such as shape, size, texture, shadow, association and more. The software also encapsulates vector processing operators to produce data which can be used in a GIS with minimal post processing.

IMAGINE Objective supports both discrete, single feature object detection as well as multi-class, wall-to-wall object-based classifications. IMAGINE Objective has been successful extracting single feature objects including residential rooftops, commercial and industrial buildings, road centerlines and/or ribbons, tree crowns, automobiles, boats, and military targets, such as airplanes and tanks, to name a few. Multi-class wall-to-wall classifications are supported for general landcover mapping and vegetation mapping applications.

IMAGINE Objective handles the ingestion and fusing of different types of geospatial data including remote sensing imagery, GIS data in both raster and vector formats, scanned paper maps, terrain data including LIDAR and LIDAR derived data, and polygon-based templates for use when appropriate. Generally speaking, the more information a user can provide the IMAGINE Objective feature model, the more accurate the results.

This aspect of information content also applies to the spatial, spectral, and radiometric resolution of the imagery as well. Spatial resolution, normally measured as the pixel size, is extremely important to a feature model's accuracy. When an object from a low spatial resolution image is converted to a polygon, the pixel artifact noise in the vertices makes shape recognition problematic and unreliable. So, in general, a feature model's accuracy will scale with the spatial resolution of the imagery.

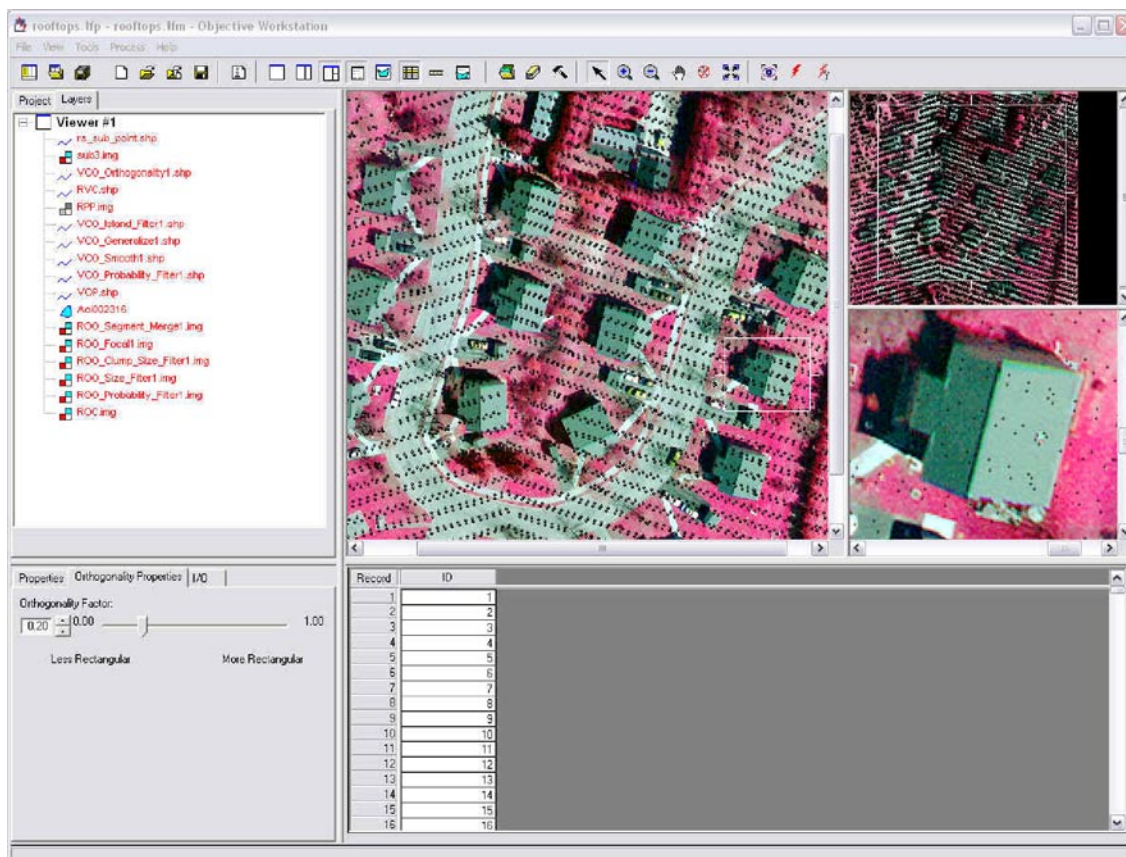
The spectral resolution, or the number of bands and wavelength mappings, are also important but perhaps less so than spatial resolution. IMAGINE Objective can be successful in single band, monochrome imagery but for most features, accuracies will improve with three to four band true color or false color infrared imagery. For some types of feature discrimination involving specific material identification of vegetation species identification, hyperspectral imagery may be required.

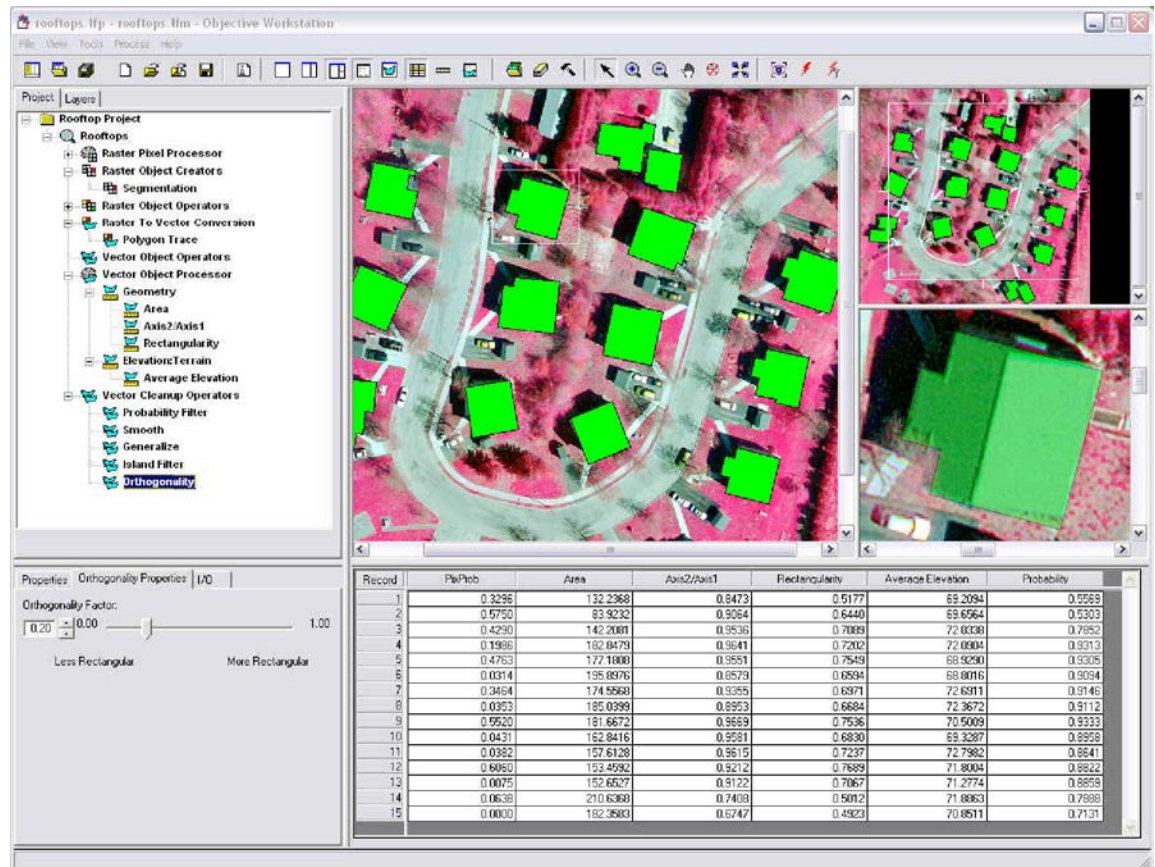
These images may have upwards of 100 spectral bands which make them suitable for imaging spectrometry algorithms. The IMAGINE Spectral Analysis Workstation should be used for these types of applications.

Radiometric resolution is somewhat less important. In most all remote sensing imagery, the pixels are collected as numbers in the 8 bit to 16 bit range. IMAGINE Objective can handle all bit depths of imagery but 8 and 16 bit are the two most common. Below are some case studies showing examples of how IMAGINE Objective and other ERDAS IMAGINE tools can potentially be used to solve a variety of common mapping problems.

### Locate and Classify Buildings/Structures, Estimating Area and Height

IMAGINE Objective can be utilized to extract and identify discrete feature objects in remotely sensed imagery. It can also ingest terrain data layers (as from LIDAR) to aid in, and improve the accuracy of, the extraction process. In the following example, IMAGINE Objective is used to extract residential rooftop footprints. The imagery used is a three band false color infrared image with 0.16 meter pixels. A 3D point shapefile derived from a LIDAR point cloud was also used.





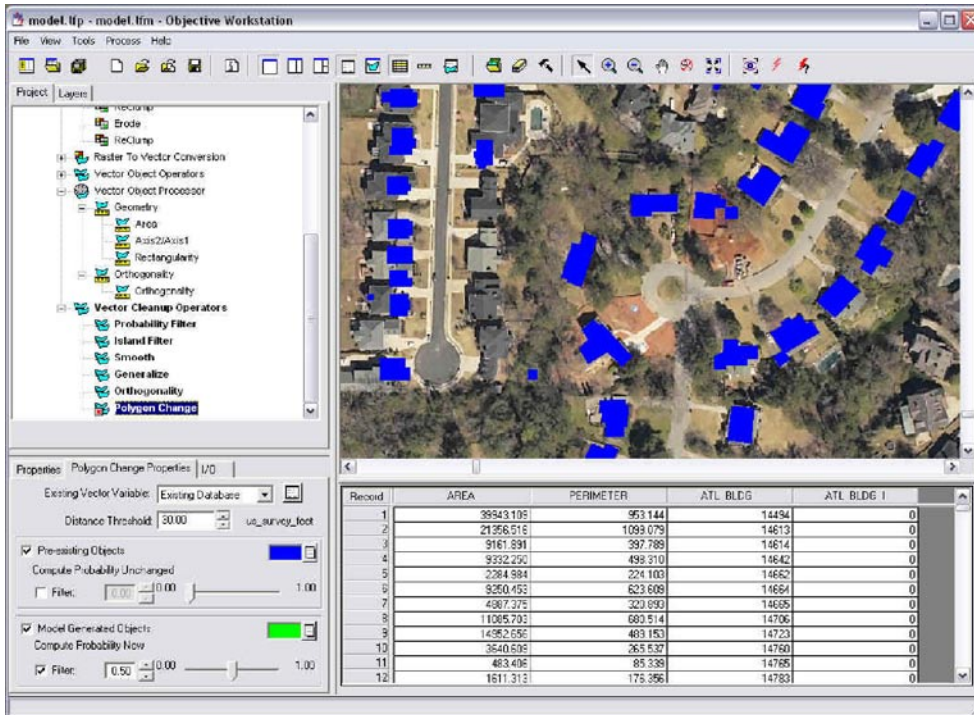
Primary rooftop extraction with area and height estimates is the final product. But because high spatial resolution imagery is used, plus the inclusion of elevation data, the accuracies of the rooftop footprints are very high. This will make it possible to do multi-date rooftop footprint comparisons and automatically compute attributes such as probability of rooftop damage or percent of a rooftop still intact.

### Locate and Classify Changes

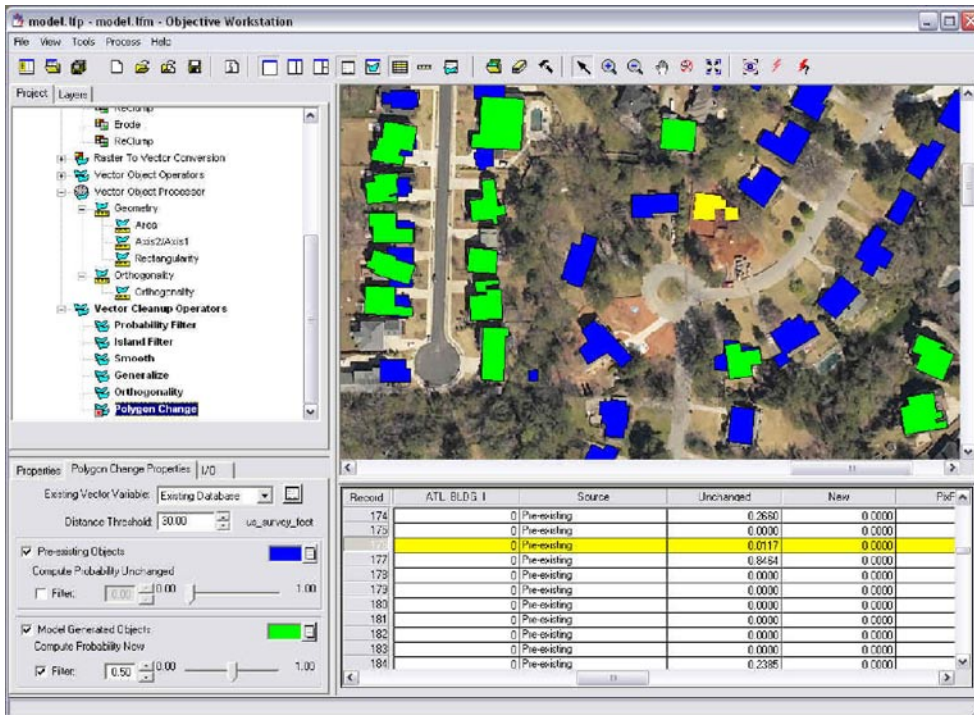
This example procedure identifies changes in residential rooftops between an existing database and features extracted from new imagery. It first does a primary rooftop extraction from a newly acquired high resolution (1.25 feet pixel) three band, true color image. Then in the final vector operator, it opens a pre-existing file containing rooftops, compares the new set of rooftops to the old, and creates a new rooftop output file containing both sets of rooftops.

Additionally, the probability attributes for the pre-existing rooftops indicate whether it is unchanged in the new image. Probability attributes for the new rooftops indicate whether it is an entirely new rooftop.

For the purposes of disaster damage assessment, the primary interest would be in finding structures in the pre-existing file but are not in the new image. The images below show the old, pre-existing rooftops. Note several roofs in the image are not in this data set. There is also the condition where a roof exists in the old data set but not in the new.



Record	AREA	PERIMETER	ATL BLDG	ATL BLDG I
1	39543.195	953.144	14494	0
2	21356.015	1099.079	14613	0
3	9161.891	397.769	14614	0
4	9332.290	499.310	14642	0
5	2284.984	224.100	14662	0
6	9250.453	623.608	14664	0
7	4987.375	320.890	14685	0
8	11065.703	680.514	14706	0
9	14962.656	483.153	14723	0
10	3640.609	265.637	14760	0
11	483.406	85.338	14785	0
12	1611.313	175.356	14783	0



Record	ATL BLDG I	Source	Unchanged	New	PctF
174	0	Pre-existing	0.2650	0.0000	
175	0	Pre-existing	0.0000	0.0000	
176	0	Pre-existing	0.0117	0.0000	
177	0	Pre-existing	0.8454	0.0000	
178	0	Pre-existing	0.0000	0.0000	
179	0	Pre-existing	0.0000	0.0000	
180	0	Pre-existing	0.0000	0.0000	
181	0	Pre-existing	0.0000	0.0000	
182	0	Pre-existing	0.0000	0.0000	
183	0	Pre-existing	0.0000	0.0000	
184	0	Pre-existing	0.2385	0.0000	

The green polygons represent rooftops that did not exist or changed significantly from the old dataset. The yellow highlighted polygon is a rooftop that existed in the old dataset but was not found in the new image.

### Measure Distances between Features of the Same Class

Measuring the distance between objects of the same feature type (i.e. residential rooftops) is relatively trivial once the method of measurement and scope of the number of objects under consideration at any one time are determined. The simplest method for measurement is the Euclidean distance, measuring between the center of gravity coordinate of each object. This is how the Polygon Change operator determines if two objects (one generally representing the “before” or existing object and the other being the “after” or newly extracted object) are to be considered the same. A more sophisticated approach would find the shortest distance between edges of the polygon objects.

Another consideration is the scope of objects. For each base object it would be possible to find the distances to:

- All other existing feature objects in the study area, resulting in a potentially large table of distance values
- The nearest N objects and their distances and directions
- All objects within a radius distance of M and their distances and directions
- The single nearest object and its distance and directions

### Measure Distances between Features of Different Classes

Measuring the distance between objects of differing feature types is also simple once the method of measurement and the number of objects under consideration is determined. Measuring feature objects to a single different feature (i.e. the shoreline) defines the scope to a single distance measurement.

### Locate Water Pooling

Water in a constrained location (i.e. pooling on a roof or parking lot) is relatively easy to extract automatically. Water usually is spectrally dissimilar to its immediate background, and the pools usually have certain size and shape characteristics. The task of identifying these pools involves building one IMAGINE Objective feature model for the water pools themselves and another for the background feature (i.e. parking lots). It is then possible to classify only the pools of water in a parking lot by using an association cue of surrounding or adjacent objects.

### Identify Pixel Material using IMAGINE Spectral Analysis

Hyperspectral images have many bands (more than 40 bands). Compared to multi-spectral images (seven or less bands), each pixel in hyperspectral images contains much more spectral information. IMAGINE Spectral Analysis uses that bountiful spectral information in the hyperspectral images to perform tasks such as Target Detection, Anomaly Detection, Material Mapping and Material Identification.

In the following example, the Material Mapping tool in IMAGINE Spectral Analysis is used to identify pixels of asphalt material. Two screen-shots are attached here. The first one shows the original image in the embedded viewers. The reference spectrum, Sample 1 in the Material List 1, is obtained from the image by selecting a point on an asphalt road (the point marked with a red target symbol). The second screen shot shows the results of Material Mapping using the Constrained Energy Minimization algorithm. It is clear that pixels on the roads are much brighter than the other pixels, simplifying the process of extracting that material as a feature map.

