

Feature Extraction from High-Resolution Remotely Sensed Imagery using Evolutionary Computation

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1. Introduction

Feature extraction, in the context of remote sensing, can be defined as image processing techniques to identify and to classify mutual relationships or mutual meaning between image regions (Baatz et al., 2000). The aggregation of image pixels forming image regions and their relationship to other image regions are interpreted and used as cues in the information retrieval process (Quackenbush, 2004). A common approach is to create hierarchical structures of image regions in which fine-scale image regions constitute portions of other coarse-scale image regions (Niemeyer & Canty, 2001). Feature extraction differs from traditional pixel-based remote sensing image classification algorithms in which each, individual pixel (or pixel vector in the case of images with more than one channel) is individually evaluated and assigned to one class (Lillesand & Kiefer, 2000). The difference between low-level information extraction techniques using traditional pixel-based classification methods and high-level information extracted by a human analyst is often referred to as the “*semantic gap*” (Smeulders et al., 2000). Human analysts use a complex combination of different image cues such as colour (spectral), texture, shape (geometry of image regions), and context (relationship between image regions). However, human analysis of large areas and multiple images is costly and time consuming (Munyati, 2000).

As the volume of available remotely sensed imagery increases by many orders of magnitude, one of the challenges faced by many organizations and institutions is converting large quantities of images into actionable information and intelligence. Because human analysis of large areas and sometimes over multiple periods of time is costly and time consuming, scientists have recognized the importance of developing more sophisticated semi-automated or automated feature extraction techniques to improve the information extraction process. The challenge resides in multifaceted problems where the relationship between image’s regions is too complex to be solved by explicit programming (hard computation) and/or these problems require the system to adapt and evolve when image conditions change. This provision is particularly important in remote sensing applications due to changing factors such as variation in sensor spatial and spectral resolutions, change in environmental conditions between images, and specificity of the feature of interest.

The use of stochastic algorithms to address these complex feature extraction problems, are now being investigated as a possible alternative; due to their properties of deriving

solutions from a small set of positive and negative examples through an optimized combinatorial search rather than being explicit programmed (Fogel, 2000; Mitchell, 1997). Evolutionary algorithms (also referred to as evolutionary computation) have been used to solve problems in different domains, including remote sensing applications.

In this chapter, the use of evolutionary algorithms, in the form of genetic programming, to aid the feature extraction process from high-resolution satellite imagery was evaluated. A novel framework involving genetic programming, standard image processing methods, and clustering algorithms is described. The proposed system was designed to support routine feature extraction procedures from satellite imagery and is composed of two modes: development and operational. In the development mode, a single and representative image in conjunction with human analyst input are used to train the system to develop the candidate solutions. The operational mode applies the developed candidate solutions to unforeseen images in an automated fashion, thus expediting the information extraction process. In this study, the objective was to quantitatively assess the generalization capability of the proposed system to imagery variations in physical and environmental factors such as distinct features with similar spectral signatures, variations in sensor's resolution, and environmental condition changes between scenes. The proposed methodology uses a biologically-inspired framework to extract and combine in non-linear way, image derived information such as colour (spectral characteristics) and shape (image region geometrical properties). The accuracy of the framework was quantitatively assessed through a cross-evaluation procedure where a set of different image chips is used to develop candidate solutions in one scene (development mode) and then test those solutions in the remaining unforeseen scenes (operational mode).

2. Background

2.1 Remote sensing and remote sensing spectral indices

Remote sensing can be defined as the science of deriving information about a feature, an object, or a phenomenon from a distance by analyzing the energy reflected or emitted by the feature (Aronoff, 2005; Lillesand & Kiefer, 2000). The main energy detected by remote sensing systems is electromagnetic energy. Remote sensing uses sensors to measure the amount of electromagnetic energy exiting an object or a geographic area. Remote sensing sensors are characterized by different resolutions such as spatial (relative ground sampling distance of one pixel), spectral (number of electromagnetic regions sampled), radiometric, and temporal (revisit time).

Because objects and/or features at the Earth's surface interact differently with the electromagnetic energy based on their molecular composition, differences in the amount and properties of electromagnetic radiation becomes a valuable source of information. Through the use of multiple parts of the electromagnetic spectrum, represented by multiple channels in remote sensing images, it is possible to generate spectral signatures and/or data transformations to aid information retrieval.

Spectral band indices are the most common spectral transformations used in remote sensing. These spectral indices apply a pixel-to-pixel operation to create a new value for individual pixels according to some pre-defined function of the spectral values (Momm et al., 2006). After the transformation, some features and/or spectral properties become more discernable when compared to the original data (Figure 1).

The challenge resides in the development of such spectral indices. The use of existing indices in new environments or the development of new spectral indices constitutes a time consuming and complex problem (Momm et al., 2007). Different features with similar spectral signatures add to the complexity of creating such indices. Spectral indices level of complexity varies according to the relationship between feature's spectral responses to different parts of the electromagnetic spectrum.

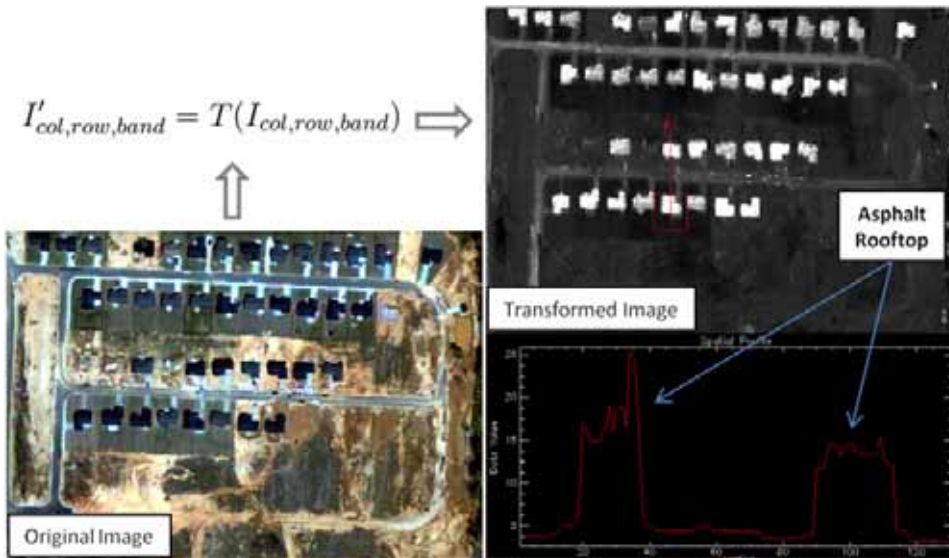


Fig. 1. Illustration of the use of spectral indices to transform the original multi-spectral image for enhanced information extraction. Example shows a spectral profile of the transformed image highlighting asphalt-based residential rooftops.

2.2 Evolutionary algorithms for remote sensing feature extraction

Easson and Momm (Easson & Momm, 2010) have provided a detailed survey of the use of evolutionary algorithms to extract information from remotely sensed data. In their review, the different applications were classified into four categories according to the general research objective: image enhancement, image classification, modelling, and feature extraction. Their literature investigation also revealed that the majority of applications are based on genetic algorithms (GA) and genetic programming (GP).

In image enhancement categories the applications described used GA and GP as an optimization tool to improve some image processing problem by defining which basic image processing operation, or sequence of operations, to use to solve the problem. The objective of image classification algorithms is to automatically (or semi-automatically) categorize all pixels in an image into classes (Lillesand & Kiefer, 2000) based on multi-dimensional spectral similarities of electromagnetic measurements at various wavelengths. The use of evolutionary algorithms to aid satellite image classification is the most common problem addressed and more than 15 publications were identified. In the modelling category, evolutionary algorithms were used to optimize the search for model's parameters or to define new models designed to obtain measurements from remotely sensed imagery.

Specifically for feature extraction applications, literature investigation indicates that this field of research is relatively new and unexplored. Daida and others (Daida et al., 1995; 1996) used genetic programming to identify pressure ridges in Arctic ice through the use of synthetic aperture RADAR images. In this work, a set of texture-based filters (convolution functions) were considered and genetic programming was used to select the most appropriate filter (or combination of filters) to highlight pressure ridges. Similarly, Howard and Roberts (Howard & Roberts, 1999) used a combination of image regions statistics, texture-based filters, and genetic programming to develop a vehicle and ship detector. In this work a two step process was used, object location and object classification. Recent contributions have employed evolutionary algorithms in the task of deriving ontology rules describing characteristics and relationships between image regions (Durand et al., 2007). The ultimate goal is to develop tools to partially replicate the human ability to interpret images (Easson & Momm, 2010). Forestier and others (Forestier et al., 2008) researched the use of genetic algorithms to optimize the search for ontology rules to segment satellite imagery. Candidate solutions, composed of non-linear combinations of the primitive rules developed by genetic algorithms, were then compared to human-derived ontology rules. The definition of ontology rules for feature extraction from remotely sensed data is a complex and time consuming task and the use of evolutionary algorithms to optimize the search and definition of such rules are now the subject of ongoing research (Forestier et al., 2008; Momm et al., 2009; Puissant et al., 2007).

3. Evolutionary framework

3.1 Framework description

The proposed framework develops spectral indices, in the form of mathematical expressions of the original image's channels, to create a transformed image; which maximizes the performance of standard classification algorithms to separate the target feature from the remaining image background (Momm et al., 2009). The system works in a learn-from-examples approach where positive and negative samples are used by the genetic programming algorithm to evolve candidate solutions through an optimized iterative search.

In the development mode, the system requires three inputs: original image, parameters controlling the run, and reference image (Figure 2). The original image consists of a representative multi-spectral image containing the feature to be extracted. Success of machine learning algorithms are dependent on the quality of the training set; and therefore, when designing applications involving feature extraction it is necessary to understand the sensor's limitations (spectral, spatial, and radiometric resolutions) and contrast them with the feature's spectral and spatial characteristics. The parameters controlling the run involve the definition of the terminal set (image's spectral channels), function set (list of basic mathematical functions used as the building blocks to evolve candidate solutions), population size, number of generations, percentage of crossover, stopping criteria, and restarting threshold (measure to maintain diversity during the evolutionary process). Reference data consists of human classified set of positive and negative samples.

During the initial generation, genetic programming randomly generates a set of candidate solutions (mathematical expressions) referred to as population. This set of candidate solutions are then individually applied to the original multi-spectral image resulting in a new set of transformed images; which are individually clustered and compared to the reference image for fitness computation. If either of the stopping criteria are met (fitness threshold or maximum number of iterations) the system sorts the candidate solutions by

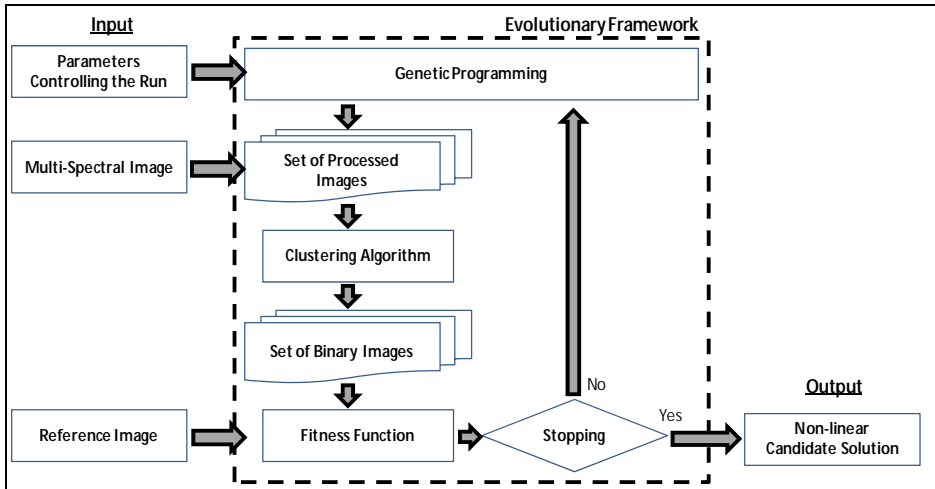


Fig. 2. Simplified flowchart illustrating data/parameters input, output, and main internal components of the evolutionary framework.

fitness values and then outputs the most fit candidate solution. On the other hand, if the stopping criteria are not met, the system performs genetic operations (cross over and restarting) with the top most fit individuals to create a new population and the entire process is iteratively repeated until the stopping criteria are met.

3.2 Fitness function

Cohen’s kappa coefficient of agreement was selected as the statistical measurement of fitness for each candidate solution (Cohen, 1960). When comparing the binary image obtained by clustering of the transformed image to the user-provided reference data, kappa is preferred over simple measure of percent of agreement because it corrects for the amount of agreement due to chance. Kappa statistics can be computed as:

$$k = \frac{N \left(\sum_{i=1}^r X_{ii} - \sum_{i=1}^r (X_{i+} * X_{+i}) \right)}{N^2 - \sum_{i=1}^r (X_{i+} * X_{+i})} \tag{1}$$

In this equation, after computing the contingency table (Jensen, 1996), *r* represents the number of rows, *X_{ii}* the sum of values in the major diagonal, *X_{i+}* the sum of observations in row *i*, *X_{+i}* the sum of observations in column *i*, and *N* the total number of observations.

3.3 Multi-stage implementation and candidate solution representation

The objective of using a sequence of steps to extract the desired information from imagery is based on the premise that complex problems can be partitioned into a series of easier-to-solve smaller problems. In theory, machine learning algorithms can master smaller tasks and when combined, the set of specialized algorithms can outperform an algorithm designed to solve the overall problem. Following this concept, the initial stages are designed to address spectral characteristics while in the latest stage geometric properties of group of connected pixels (image objects) are considered. Each subsequent stage uses as input the results of the previous stage.

The initial steps address the identification of pixels with similar spectral characteristics to the feature of interest. Ontology rules are not considered since, after the mathematical transformation of the image, pixels are individually analyzed and classified. Transformation functions, also referred to as spectral indices, use the image spectral channels as arguments (Figure 3).

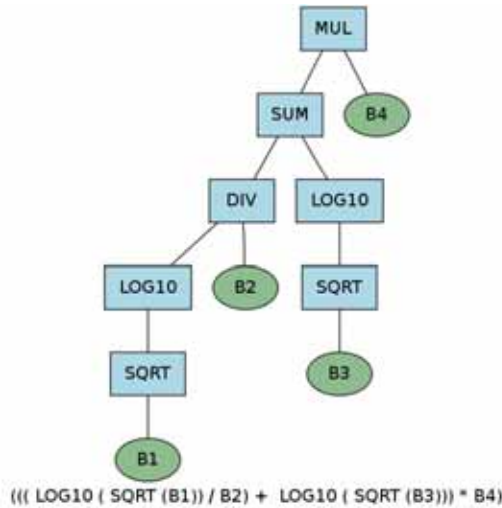


Fig. 3. Example of genetic programming candidate solution representation as a hierarchical tree structure (internal) and as a mathematical expression (external) used in the spectral pixel classification stages of the feature extraction process.

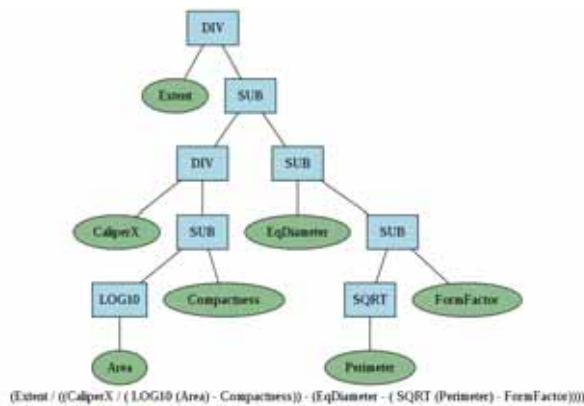


Fig. 4. Example of genetic programming candidate solution representation as a hierarchical tree structure (internal) and as a mathematical expression (external) used in the geometric stages of the feature extraction process. Arguments are geometric properties of image objects.

In the final stages, the classified image resulted from previous stage is processed to identify groups of connected pixels (segmentation), label each group of connected pixels with a unique identifier, and computation of multiple geometric descriptors (Momm et al., 2010).

The input for the geometric stage consists of a raster grid image with the number of image object as the number rows and the number of shape descriptors as the number of columns. Candidate solutions in the geometrical stages use as arguments the geometrical shape descriptors (Figure 4).

4. Feature extraction experiment

The overall research objective is to develop a system to be used in routine operational situations by extracting specific information from sets of imagery with minimum human interaction possible. The ideal system should be trained using a small and representative scene and once the solutions are developed, these solutions are then used in a multitude of unforeseen scenes in an automated fashion. In this experiment, the generalization ability of the evolutionary framework is assessed when candidate solutions are applied to different images with changing environmental conditions and remote sensing parameters. The aim of this study is to use its outcome as guidance for future applications by identifying the limitations and strengths of the proposed system.

The problem selected in the evaluation of the evolutionary framework was the identification of residential single family rooftops from high spatial resolution imagery. There are some challenges in the development of algorithms to obtain such information. The limited spectral resolution presented by the current high spatial resolution satellite sensors combined with the spectral similarities between asphalt-based roofing material and asphalt pavement limits the use of pixel-by-pixel classification algorithms. To overcome the spectral similarities limitations, a geometric classification of the spectrally classified material is introduced mimicking the human analyst classification approach. Human’s advanced interpretation ability takes into consideration not only rooftop colour information (spectral information) but also our knowledge of rooftop geometry.

Our approach divided the task of identifying single family residential buildings (through rooftop) into three stages (Figure 5). In the first stage, the evolutionary framework is used to evolve spectral transformation to spectrally separate the image pixels into two classes, asphalt-based material and background. Using the results from the first stage, the evolutionary framework is used to evolve a new set of spectral transformation to further separate the pixels previously identified as asphalt-material into either rooftop class or other classe. The third stage obtains geometric properties of each group of connected pixels

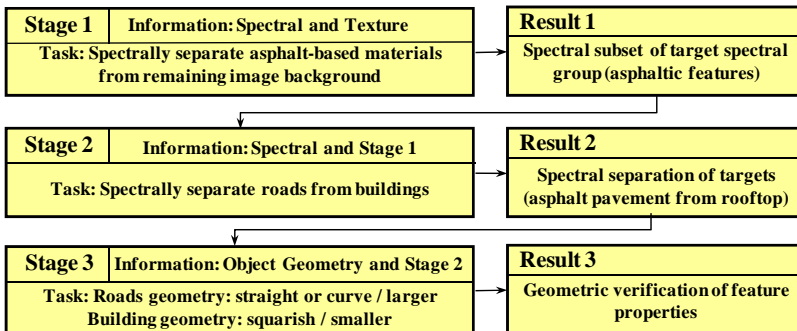


Fig. 5. Flowchart of the multi-stage approach for single family rooftop detection to access the evolutionary framework’s ability to generalize as remote sensing and physical conditions change.

identified as single family rooftop and the evolutionary framework is once again used to evolve a third set of mathematical transformations to distinguish single family residential rooftop from other features (such as commercial buildings, pavement, etc) based on geometric properties (Momm et al., 2010).

Examples of the resulting thematic maps from each stage are displayed on Figure 6. The resulting map of stage 1 (step 1 in Figure 6) illustrates the separation between asphalt-based materials (in red colour) and the remaining background (green colour).

The map resulting from stage 1 is fused with the original multi-spectral image to create the input image for stage 2. Green colour pixels in Figure 6 step 1, are used as a filter to mask out pixels from the original multi-spectral image leaving only the pixels marked with red. A new multi-spectral image is created with the same original four channels but pixel can have as values either the original scaled radiance values (red pixels from map created in stage 1) or no data (green pixels from map created in stage 2). The results from stage 2 further discriminate asphalt-based materials into rooftops and others (step 2 in Figure 5). In the middle map, black colour indicates pixels not considered (masked out), red colour indicates target material, and green colour non rooftop materials.

In the final stage, the group of connected pixels resulting from stage 2 (red colour in the map created in stage 2) are further filtered based on geometric properties such that smaller, larger, and elongated image objects differing from single family residential building were removed (step 3 in Figure 6).



Fig. 6. Illustration of the outcomes produced by the evolutionary framework for each step considered. Step 1 outputs a binary image containing asphalt-based material and background. Step 2 uses the results of step 1 to generate another image discriminating asphalt rooftop from other asphalt-based material. Step 3 uses the output from step 2 containing group of connected pixels and filter them based on geometric properties.

4.1 Data description and preparation steps

Three scenes were used in this experiment, two obtained with the IKONOS sensor and one with the QuickBird sensor (Table 1). The two IKONOS scenes were acquired three years apart during early fall while the QuickBird scene was acquired during the summer. The 2005 imagery was immediately acquired after hurricane Katrina. Trees in the region investigated (south part of Mississippi in the United States of America) does not lose their leaves during the winter; however, there are differences in rain patterns and day light illumination (Table 1).

Scene	Sensor	Acquisition Date	Spatial Resolution (meters)	Spectral Resolution (η meters)	Scan Azimuth.	Sun Elevation.	Sun Azimuth.
1	IKONOS-2	2002-OCT-06	Pan: 1.0 Multi: 4.0	480,550, 665,805	179.97	50.82	154.94
2	IKONOS-2	2005-SEP-06	Pan: 1.0 Multi: 4.0	480,550, 665,805	90.00	63.24	107.5
3	QuickBird	2002-JUL-06	Pan: 0.7 Multi: 2.8	485,560, 660,830	25.55	70.22	144.20

Table 1. Imagery used in the evaluation of the evolutionary framework in the task of single family residential rooftop extraction.

The scenes also differ in the sensor’s spatial and spectral resolution. QuickBird has a nominal spatial resolution of 0.7 meters for the pan-chromatic image and 2.8 meters for the multi-spectral image while IKONOS has 1.0 meter and 4.0 meters for pan-chromatic and multi-spectral images respectively. Both sensors record four spectral channels (blue, green, red, and infra-red) with similar nominal central wavelengths. The largest differences are in the infra-red channel.

All image scenes were provided as scaled radiance at the sensor. An enhanced image was generated by fusing the high spatial resolution pan-chromatic image to the multi-spectral image using the Gram-Schmidt technique (Laben & Brower, 2000). These images were further subset for the generation of image chips (Table 2) to cope with the large computational cost

CHIP Identification	Nominal GSD (meters)	Number of Samples	Number of Lines	Number of Bands	Role
QB02R2	0.7	623	614	4	Training and Testing
QB02R5	0.7	517	677	4	Training and Testing
IK03R1	1.0	242	233	4	Training and Testing
IK02R2	1.0	436	425	4	Training and Testing
IK05R1	1.0	242	233	4	Training and Testing
IK05R2	1.0	436	425	4	Training and Testing
QB02C1	2.8	581	459	4	Testing
QB02C2	2.8	348	475	4	Testing
QB02C3	2.8	646	400	4	Testing
IK05C1	1.0	866	478	4	Testing

Table 2. Description of the image chips characteristics and primary role in the cross-validation process of the evolutionary framework.

involved during developing mode (training). Image chips QB02C1, QB02C2, and QB02C3 were produced using the original multi-spectral image before the resolution enhancement procedure. Each image chip covers areas with different morphological characteristics, environmental conditions, and level of pre-processing (Figure 6 and 7). A summary of the environmental and physical property differences between image chips can be listed as follows:

- **Level of oxidation of the asphaltic material.** Asphalt-based pavement and roofing material are subject to chemical oxidation over time by prolonged exposure and reaction with atmospheric oxygen leading to changes in electromagnetic reflectance properties. Roofing material in image chips QB02R2 and QB02R5 present contrasting levels of oxidation, thus indicating the presence of younger housing rooftop in the QB02R2 image chip.

- Level of tree coverage of rooftops: Tree canopy coverage of rooftops varies at each residential subdivision. This poses a challenge for the geometric stage where the rectangular shape of residential rooftops may be altered by tree cover.
- Rooftop integrity: Image chips IK05C1, IK05R1, and IK05R2 cover locations impacted by hurricane winds leading to varying levels of rooftop damage ranging from missing shingles to flattened rooftops.



Fig. 6. Image chips used in the evaluation of the evolutionary framework in the task of identifying single family residential rooftops through training and testing procedure. Differences in sensors, acquisition dates, and level of pre-processing were exploited to access the generalization ability of the system to changing conditions.

Reference data was generated by manual classification of individual pixels into one of the three land use covers: rooftop, roads, and other (Figure 8). In the first stage (asphalt material versus background) the land use covers rooftop and roads were combined to form another class, asphalt-based material. The reference data used as input for stage two uses only rooftop and road classes.

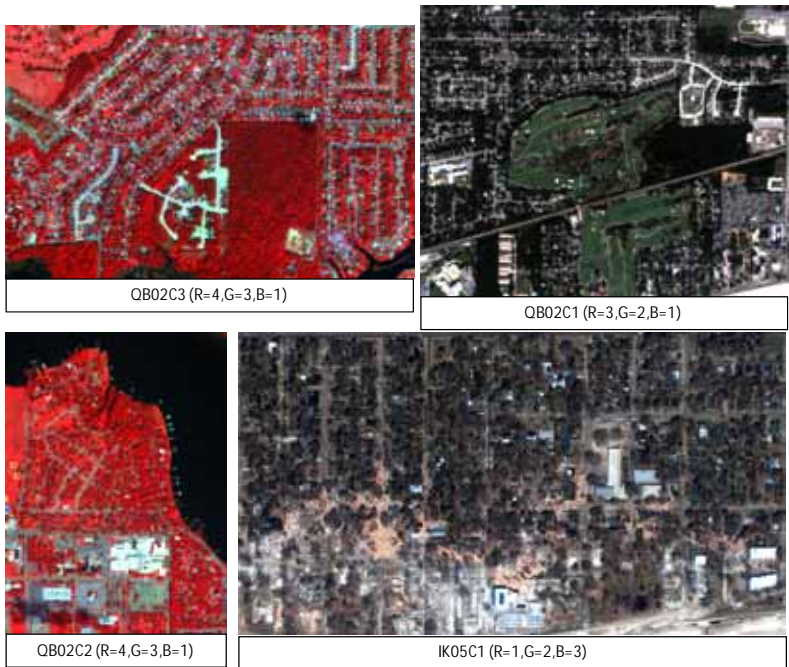


Fig. 7. Additional image chips used in the evaluation of candidate solutions developed by the evolutionary framework for identifying single family residential rooftops.

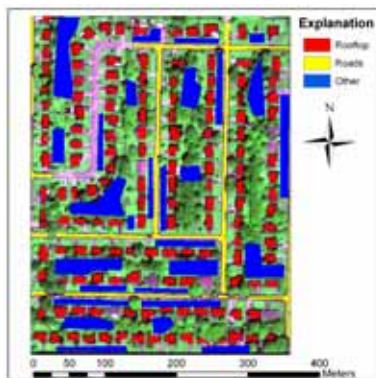


Fig. 8. Example of coloured polygons representing the reference datasets obtained by manual classification of individual image pixels. Background shows QB02R5 with spectral band combination 1-4-1.

The reference data for stage 3 (geometric properties) used the set of resulting images from stage 2. These thematic images were analyzed by human analyst and individual image objects were classified as either residential single family rooftop or other.

4.2 Genetic programming parameters

Two configurations of genetic programming parameters were considered (Table 3). For the first two stages, dealing with spectral information, the terminal set was composed of the four available spectral bands. This configuration used a reduced number of generations and a smaller population size. These were required to cope with the increased computational overhead generated by the utilization of images as arguments in the candidate solutions. During the evolutionary process, calculation of fitness values are formed by a sequence of mathematical expressions where the attributes consist of images that must be processed thousands or even millions of times depending on the population size and the number of generations. Conversely, the number of image objects is many orders of magnitudes smaller than the number of pixels, allowing for the larger population sizes and number of generations. The terminal set in the third stage contains ten geometric descriptors (Table 4). In both scenarios, constant numbers were not considered as part of the terminal set to promote adaptation and generalization. Constant numbers, selected during the evolutionary process as being part of the solution, are often specific to the training image and thus considered a threat to the generalization ability of the system when the same solution is applied to a different image. It is possible that, in the testing image, the constant number defined during training has a different meaning.

Parameter	Spectral Information	Geometric Information
1. Terminal Set	Image spectral bands	Object's shape descriptors
2. Function Set	Summation (SUM) Subtraction (SUB) Safe Division (DIV) Multiplication (MUL) Safe Square Root (SQRT) Safe logarithm (LOG) Absolute value (ABS)	Summation (SUM) Subtraction (SUB) Safe Division (DIV) Multiplication (MUL) Safe Square Root (SQRT) Safe logarithm (LOG) Absolute value (ABS) Threshold (<i>if a>b then a else b</i>) Greater than (<i>if a>b then 1 else -1</i>) Lower than (<i>if a<b then 1 else -1</i>)
3. Fitness Function	Kappa Coefficient of Agreement	Kappa Coefficient of Agreement
4. Population Size	40	200
5. Generations	70	250
6. Crossover	30%	30%
7. Stopping Criteria	71 or $K^{\text{hat}} > 0.975$	251 or $K^{\text{hat}} > 0.975$
8. Restarting Threshold	5 generations	5 generations

Table 3. Genetic programming parameters used in the multi-step feature extraction experiment. During the spectral information steps, smaller population size and number of generations were used to cope with the computational cost inherent from using multi-spectral images in the terminal set.

Population diversity was controlled by restarting procedure (Momm & Easson, 2010; Momm et al., 2008) rather than traditional mutation operations. The basic principle of restarting is the introduction of new genetic material into the evolutionary process after a certain number of iterations without change in fitness value of the *most fit* individual of the population.

Shape Descriptors			
1	Area	6	$FormFactor = \frac{4 * \pi * Area}{Perimeter^2}$
2	Caliper X	7	$Roundness = \frac{4 * Area}{\pi * (MaxDiameter^2)}$
3	Caliper Y	8	$AspectRatio = \frac{Caliper_x}{Caliper_y}$
4	Perimeter	9	$Compactness = \frac{\sqrt{4 * Area}}{\pi}}{MaxDiameter}$
5	$EquivalentDiameter = \sqrt{\frac{4 * Area}{\pi}}$	10	$Extent = \frac{Area}{Extent_x * Extent_y}$

Table 4. Shape descriptors of group of connected pixels used in the experiment of identifying residential rooftops from high spatial resolution satellite imagery.

4.3 Cross-evaluation

The evaluation of the system was performed by developing solutions in one image chip and then applying those solutions to the remaining image chips in the pool. Results generated by the system were then quantitatively compared to human classified reference data. For each stage six training-testing configurations were considered resulting in 18 different scenarios. This approach was adopted to verify the system’s robustness to environmental and physical condition changes between images.

5. Experimental results and discussion

The accuracy results for each scenario considered were expressed as overall accuracy and Cohen’s kappa coefficient of agreement. Kappa values range from -1.0 to 1.0. Negative values mean agreement less than random chance of agreement while positive values are a result of greater than random chance of agreement.

Accuracy results for each scenario are plotted in Figures 8, 9, and 10. The image chips used to develop solutions are identified by a shadowed area in the plots. The remaining points in each plot are accuracy results yielded from using the candidate solutions developed using the image chip in the shadowed area to the other image chips. For example, in the upper left plot in Figure 8, a non-linear spectral transformation was developed to spectrally identify asphalt-based materials using the evolutionary framework with the image chip QB02R2 and its correspondent reference dataset as input. The spectral transformation developed, was then applied to the remaining nine image chips resulting in nine new transformed images. Each transformed image was then clustered into a two-class thematic map and compared to its correspondent reference data for fitness computation (overall accuracy and kappa statistic).

Analysis of the accuracy results for stage 1 (Figure 8), identification of asphalt-based materials, indicates that solutions developed and tested using the sensor QuickBird produced an overall consistent pattern of accuracy results despite the differences in pre-processing between image chips. These findings were expected due to the smaller level of difficulty of this task. Conversely, training and testing results between image chips produced from IKONOS 2003 and 2005 imagery did not agree. This could be attributed to the differences in shade length and orientation between these scenes caused by distinct sun elevation and azimuth angles (Table 1).

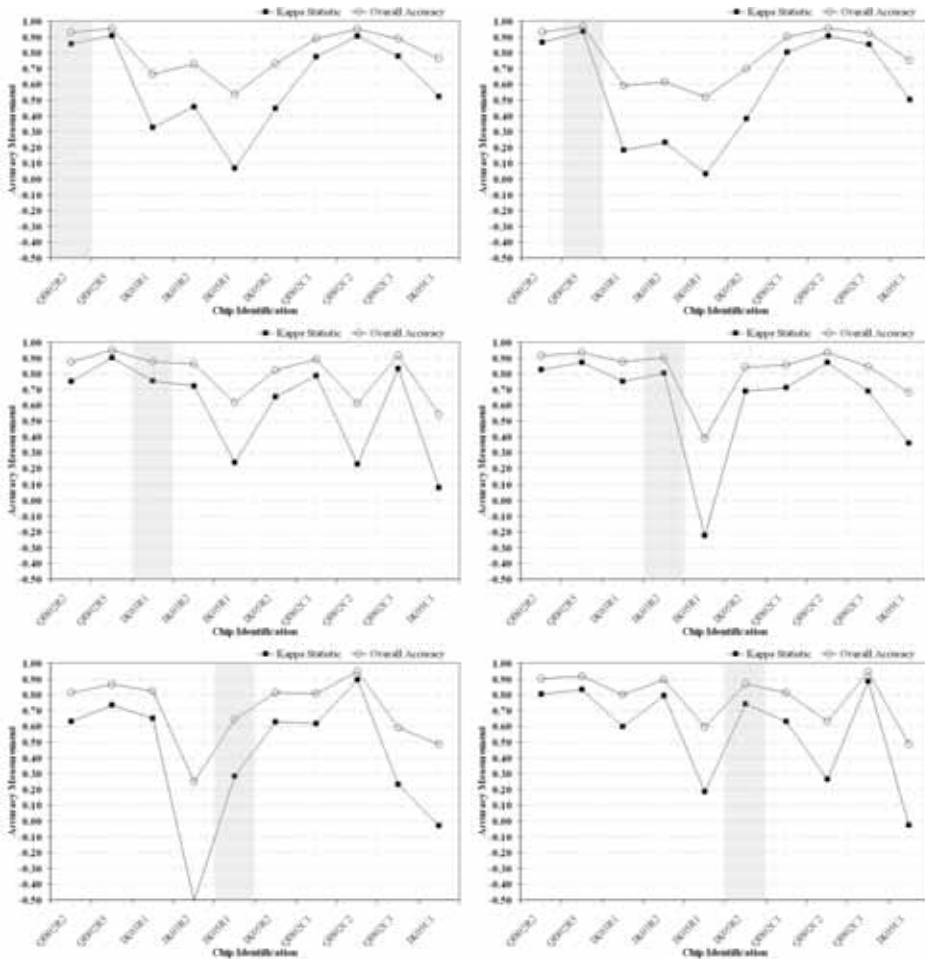


Fig. 8. Accuracy results of step 1 in the cross-evaluation of candidate solutions for imagery classification developed using the evolutionary framework. In step 1 candidate solutions were developed to spectrally classify individual pixels as either asphaltic material or background. The shadowed vertical bar represents the image chip used for training (developing the candidate solutions) and the remaining points are the testing results when using the candidate solution developed using the training image.

The thematic maps, produced in stage 1, were used to create the necessary input files for stage 2. Image chips derived from the QuickBird sensor repeated the good generalization performance previously displayed in stage 1 (Figure 9). Results also indicated that age of roofing material and roads had little or no effect in the QuickBird-based image chips. The image chip IK05R1 and IK03R2 resulted in the poorest performance.

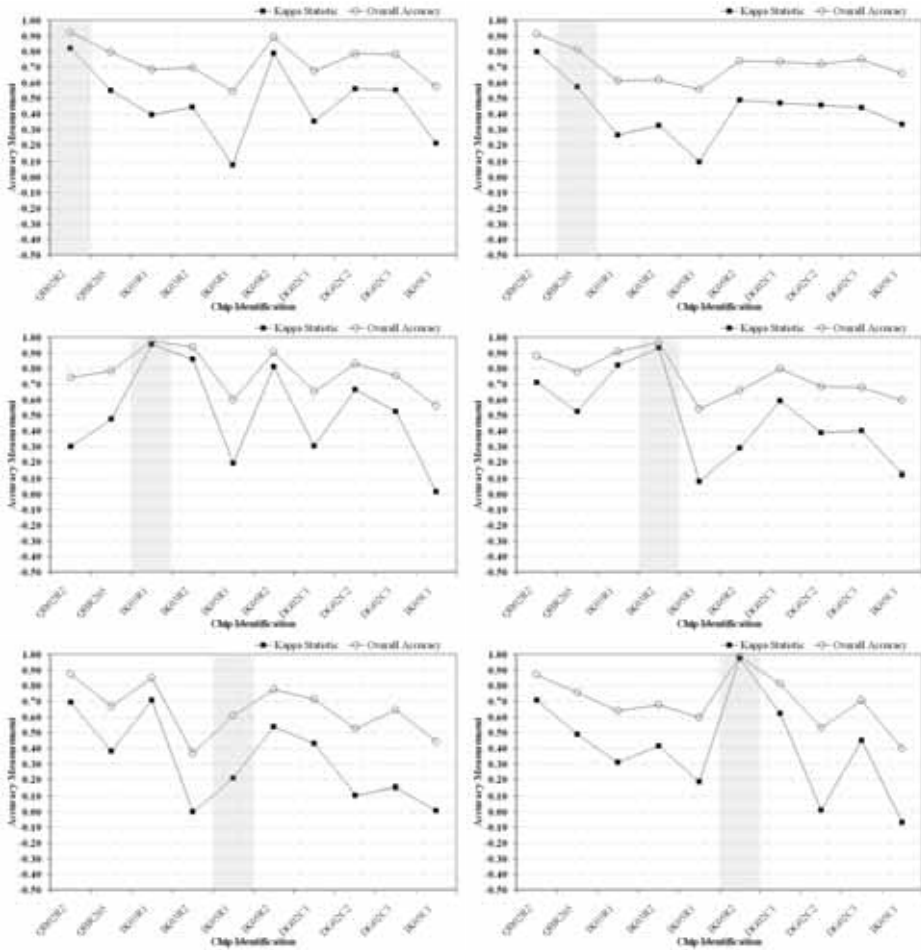


Fig. 9. Accuracy results of step 2 in the cross-evaluation of candidate solutions for imagery classification developed using the evolutionary framework. In step 2 candidate solutions were developed to spectrally classify individual pixels selected in step 1 as either asphaltic rooftop or other asphalt-based material. The shadowed vertical bar represents the image chip used for training (developing the candidate solutions) and the remaining points are the testing results when using the candidate solution developed using the training image.

The highest variability was found in stage 3, image object classification based on geometric descriptors (Figure 10), where no apparent pattern could be identified. Kappa statistics values were found in the “very good to excellent” agreement beyond the random chance of agreement range (>0.75), according to Landis and Kock (Landis & Kock, 1977), only for the image chips used in the training phase. With exception of isolated cases, results indicated a weak generalization capability of the system.

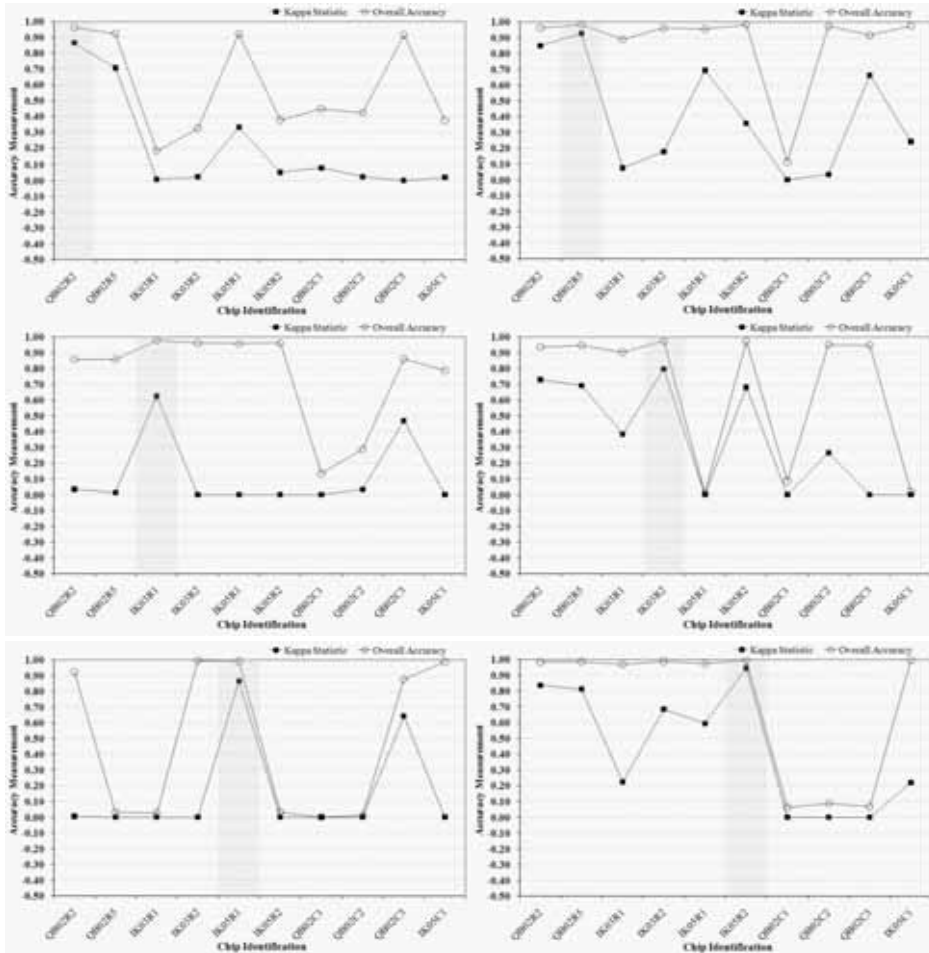


Fig. 10. Accuracy results of step 3 in the cross-evaluation of candidate solutions for imagery classification developed using the evolutionary framework. In step 3 candidate solutions were developed to geometrically identify individual group of connected pixels, classified in step 2, as single family residential rooftop. The shadowed vertical bar represents the image chip used for training (developing the candidate solutions) and the remaining points are the testing results when using the candidate solution developed using the training image.

The poor generalization ability found in Stage 3 could be partially attributed to the large variability in rooftops shapes (Figure 11) causing a direct impact on the shape descriptors. Image chips presented different pixel sizes as result of differences in sensors spatial resolution and image pre-processing procedures. For example, image object shown in Figure 11 boxes 1 and 4 have a nominal spatial resolution of 0.7 meters, boxes 3 and 6 1.0 meter, and boxes 2 and 5 2.8 meters. Additional variations in image object shapes were caused by partially coverage of rooftops by tree canopy (box 4 and 5) and roof damage caused by hurricane winds (box 3 missing shingles and box 6 half of the roofing material was removed).

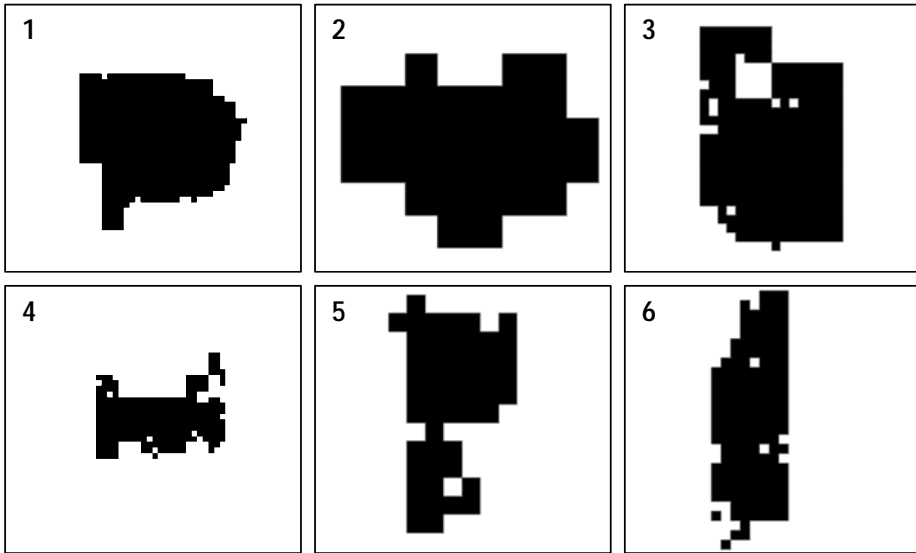


Fig. 11. Image objects representing single family residential rooftop extracted using the evolutionary framework. Image objects displayed illustrate the large variability in geometric properties due to factors such as sensor spatial resolution, rooftop partially covered by tree canopies (boxes 4 and 5), and damaged rooftops (boxes 3 and 6).

6. Conclusions

In this chapter we evaluated the robustness of an evolutionary framework in the task of feature extraction from remotely sensed imagery. The proposed system integrated standard imagery processing algorithms with genetic programming to evolve non-linear mathematical transformations to convert the original imagery into transformed images to aid in the discrimination of the material/feature of interest. The task selected was the identification of residential single-family rooftops from several image chips produced from scenes acquired with different sensors and at different dates and locations. Robustness was quantitatively assessed by training the system in one image chip and testing the evolved solutions in the remaining image chips.

The overall task of identifying rooftops from several image chips was addressed by dividing it into three sub-stages: two focused on spectral characteristics and one focused on geometrical characteristics. The multi-stage approach permitted the breakdown of a

complex problem into three simpler and smaller problems. In each sub-task a more specialized solution was evolved by the genetic programming algorithm as its performance could be assessed specifically for that sub-task. Because the results from one stage were used as input for the subsequent stage, the success of individual stages becomes significant to the overall success of the system. Additionally, the multi-stage approach helped identify possible limitations and areas of improvement of the system.

Although environmental and physical factors, such as environmental conditions, date of acquisition of the scenes, sensor resolutions, and others, influenced the robustness of the system in all stages; the main discrepancy of the results were found in the third stage (geometric properties). In the first two stages (focused on spectral information), results indicated a good agreement between sensors and a small impact of seasonal differences, illumination (radiance received at the sensor), and level of pre-processing of the scenes. The limited generalization ability demonstrated by the third stage can be partially attributed to the geometric properties dependency on sensor's spatial resolution (pixel size), type of subdivision (rooftop geometry), tree canopy coverage of rooftop, and level of rooftop damage. The complexity and size of the search space when these properties are combined limited the ability of genetic programming to evolve general solutions.

Once the development stage is completed, the operational stage has a small computational cost allowing it to be applied in a large number of scenes. The evolutionary framework was able to evolve useful non-linear transformations that provides tools to expedite the information extraction from large amounts of data, despite the limited generalization capability demonstrated by the geometrical stage. For improved generalization of geometrical stages, we advise the use of images collected with similar sensor's spatial characteristics and identification of features with similar shape properties in both training and testing images.

Future work includes the addition of more stages to investigate ontology (relationship between image objects). This relationship is inherent to the human's perception of how features should look like. For instance, the human analyst knows that a house may be connected to the road by a concrete driveway and that houses occur within a certain distance of roads. The same concept could be carried out to produce computer programs to replicate our spatial relationship perception ability. Topological functions such as "connected", "compact", "continuity", "close", "contained", and others could be defined and implemented to be used in the subsequent stages. Evolutionary algorithms could be used as the optimization tool to generate the most appropriate ontology representation of the feature of interest, using the same optimized learn-from-examples schema used herein.

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8. References

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