Digital Image Processing in Remote Sensing

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***Abstract*—Imaging systems, particularly those on board satellites, provide a repetitive and consistent view of the earth that has been used in many remote sensing applications such as urban growth, deforestation and crop monitoring, weather prediction, land use mapping, land cover mapping and so on. For each application it is necessary to develop a specific methodology to extract information from the image data. To develop a methodology it is necessary to identify a procedure based on image processing techniques that is more adequate to the problem solution. In spite of the application complexity, some basic techniques are common in most of the remote sensing applications named as image registration, image fusion, image segmentation and classification. Hence, this paper aims to present an overview about the use of image processing techniques to solve a general problem on remote sensing application. A case study on an urban application is provided to illustrate the use of remote sensing technologies for solving the problem.**

***Index Terms*—image processing, remote sensing, open source software, satellite images**

I. Introduction

The main objective of processing a digital image is for information extraction and enhancement of its visual quality in order to make it more interpretable by a human analyst or autonomous machine perception. Examples of digital images are those acquired by digital cameras, sensors on board satellites or aircrafts, medical equipments, industrial quality control equipments, etc.

Increasingly, data from multiple sensors are used to gain complete understanding of Earth processes. Various image processing technologies have been developed to deal with the challenges to extract information from remotely sensed data [1]-[4]. To build a remote sensing application, a processing procedure must be developed to process the data and, therefore, generate the expected output. Before analyzing the images, they have to be geometrically and radiometrically corrected. This processing phase, called pre-processing, is essential mainly in applications where the images are acquired from different sensors and at different times. After this phase, the images are enhanced to facilitate the information extraction. Finally, the images are segmented and classified to produce a digital thematic map.

The users have to be aware that there is not a common procedure to process the images for all applications. In order to build a remote sensing application the researcher has to have information about the data characteristics, region of interest, and the type of result he is interested in. Based on this knowledge, he figures out the most adequate image processing techniques and develops a methodology to solve the application problem. Therefore, in this paper we will provide a general view of how image processing techniques can be applied in remote sensing applications. We present basic concepts in remote sensing in Section II. Following, we present a brief review on image registration, fusion, segmentation, and classification, respectively, in Section III. To illustrate the usage of image processing techniques in a remote sensing application we show a study case on urban area analysis in Section IV. Finally, we present the conclusions in Section V.

II. Remote Sensing Concepts

Here, remote sensing is defined as the measurement of object properties on the Earth's surface using data acquired from aircraft and satellites [5][6][7]. Sensors on board satellites or aircrafts measure the amounts of energy reflected from or emitted by the Earth surface targets in different wavelength intervals (Fig. 1). Remote sensing systems, particularly those on board satellites, provide a repetitive and consistent view of the earth that is very important to monitor the earth system and the effect of human activities on the earth [1].

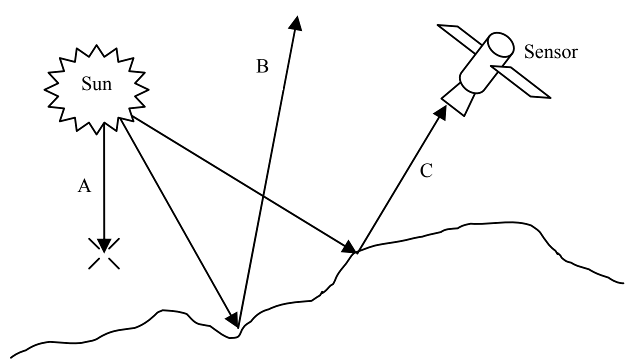

Figure 1 - Sensors measure the amounts of energy reflected from or emitted by the Earth surface targets: Absorbed (A), Scattered (B), and Reflected (C) energy (Adapted from [1]).

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A basic assumption in remote Sensing is that individual land covers (soil, water bodies, and vegetation of various species) have a characteristic manner of interacting with incident radiation which is described by the spectral response (spectral signature) of that target [2]. The spectral response is represented by a curve that describes the amount of reflected energy by the target in function of the wavelength. Fig. 2 shows the spectral signature of some common objects found in urban environments.

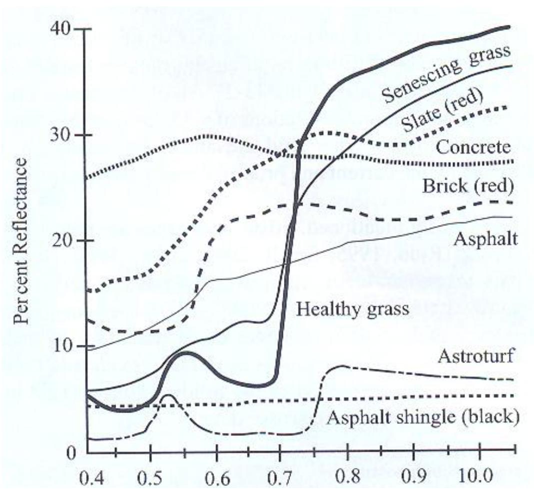


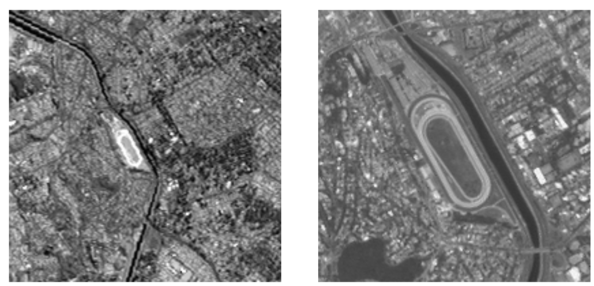
Figure 2 - Spectral responses for common materials found in urban environments [5].

The most significant characteristic of remote sensing images is the wavelength range used in the image acquisition system. Optical remote sensing systems acquire and record data from the visible to the near and mid/thermal infrared range in the electromagnetic spectrum. The energy reflected by targets on the earth can be resolved into different wavelengths that help to understand the properties of the earth surface region being imaged. The ability of a sensor to define fine wavelength intervals is described by its spectral resolution. The finer the spectral resolution the narrower the wavelength interval for a particular channel or band. As an example, camera CBERS-2B CCD [8] has 4 spectral bands from the visible to near infrared wavelengths (Table I).

Other important characteristics of remote sensing images are spatial, temporal, and radiometric resolutions. The term spatial resolution is used to refer to the size of the smallest observable object. If we can observe fine details in an image with good precision we say that this image has good resolution. The higher the spatial resolution the smaller the object one can discriminate in an image. Hence, the detector projection on Earth surface know as linear Instantaneous Field of View (IFOV) defines the spatial resolution [2],[5], [7]. Fig. 2 shows two images acquired from sensors with different spatial resolutions. Same object in the scene appears with different information details. See [7] to have more information about various sensors with different imaging characteristics.

Temporal resolution defines the time interval in which the same area on the earth is imaged by the satellite. Regular revisits are important for monitoring changes of objects (agricultural crops, urban areas, water) [5]. Radiometric resolution refers to the number of digital levels used to represent the data collected by the sensor. Each pixel is represented by a Digital Number (DN). Most images acquired from imaging systems of medium spatial resolution are represented with 256 quantization levels (equivalent to 8 bits).

In remote sensing each monochromatic image obtained in a specific wavelength range is known as spectral band. A set of bands is called multispectral image. The bands can be composed in a RGB (Red, Green, and Blue) color model and used for displaying, enhancement, and information extraction. Different color compositions can be produced by associating each band to each channels R, G, and B. For example, color composition of CBERS-2B image R3G4B2 (bands 3, 4, 2 displayed in channels R, G and B, respectively) can be employed as, for example, in urban studies. Land covers such as vegetation, buildings, and water bodies can be well discriminated using this composition. Figures 4a and 4b show examples of monochromatic and multispectral images, respectively, acquired from sensor CCD on board satellite CBERS-2B, covering an urban region of Brasilia. Table I summarizes the principal imaging characteristics of the cameras CCD and HR on board the satellite CBERS-2B.



(a) (b)

Figure 3 - Images obtained from sensors with different spatial resolutions. (a) Landsat-TM5, 30 m.; (b) Alos-AVNIR, 10 m.

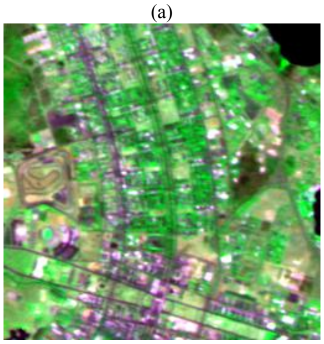
TABLE I - CHARACTERISTICS OF THE IMAGING INSTRUMENT CCD AND HR ON BOARD SATELLITE CBERS-2B [8].

	CCD Camera	HR Camera
Spectral bands	0.51 - 0.73 μm (pan) 0.45 - 0.52 μm (blue) 0.52 - 0.59 μm (green) 0.63 - 0.69 μm (red) 0.77 - 0.89 μm (near infrared)	0.50 - 0.80 μm (panchromatic)
Field of view	8,3º	2.1º
Spatial resolution	20 x 20 m	2.7 x 2.7 m
Swath width	113 km	27 km (nadir)
Temporal resolution	26 days nadir view (3 days revisit)	130 days in the proposed operation
Radiometric Resolution	8 bits	8 bits

III. IMAGE PROCESSING TECHNIQUES

For each remote sensing application a specific processing methodology must be developed. Fig. 5 illustrates the main steps of digital image processing which define the operations sequence, in general, adopted for building a methodology. Preprocessing phase consists of those operations that prepare data for subsequent analysis that attempts to correct or compensate for systematic errors. Common preprocessing techniques include atmospheric correction, noise filtering, detector calibration, geometric correction, and image registration [1], [3]. After preprocessing is complete, the analyst may use enhancement techniques to enhance the objects of interest as well as feature extraction techniques to reduce the data dimensionality. Here, we will name this step as enhancement.

(a)



(b)

Figure 4 - CBERS-2B CCD image of an urban region of Brasilia. (a) band 3; (b) color composition R3G4B2.

Feature extraction attempts to extract the most useful information of the data for further study. This phase reduces the number of variables that must be examined, thereby saving time and resources. Enhancement operations are carried out to improve the interpretability of the image by increasing apparent contrast among various features of interest to facilitate the information extraction task. Common enhancement and feature extraction techniques include contrast adjustments, band rationing, spatial filtering, image fusion, linear mixture model, principal component analysis and color enhancement [1], [4]. In general, the enhancement techniques are empirical because they depend on the imaging characteristics of data and application.

After preprocessing and enhancement steps, the remotely sensed data are subjected to quantitative analysis to assign individual pixels to specific ground cover types or classes. The class identifies the type of ground cover (water, vegetation, soils, for example). The pixels are identified based upon their numerical properties or attributes. This phase can be performed by analyzing the properties of individual pixel (per pixel) or group of pixels (region). In latter, the image is firstly segmented into a set of regions that can be described by a set of attributes (area, perimeter, texture, color, statistical information). This set of attributes is used to characterize and identify each object in the image. This operation of recognizing objects in the image is called image classification and it results in thematic maps as output.

After classification, it is necessary to evaluate its accuracy by comparing the classes on the thematic map with the areas of known identity on the ground (reference map). A reference map is created using information acquired by the user in the field work. Indexes to measure the classification accuracy such as Kappa [9] are often used. The index values ranges from 0 to 1, and values greater than 0.6 indicates a good overall result. Post-classification is an optional processing step.

In the next subsections, we will give a general view of some basic image processing techniques used in most remote sensing applications.

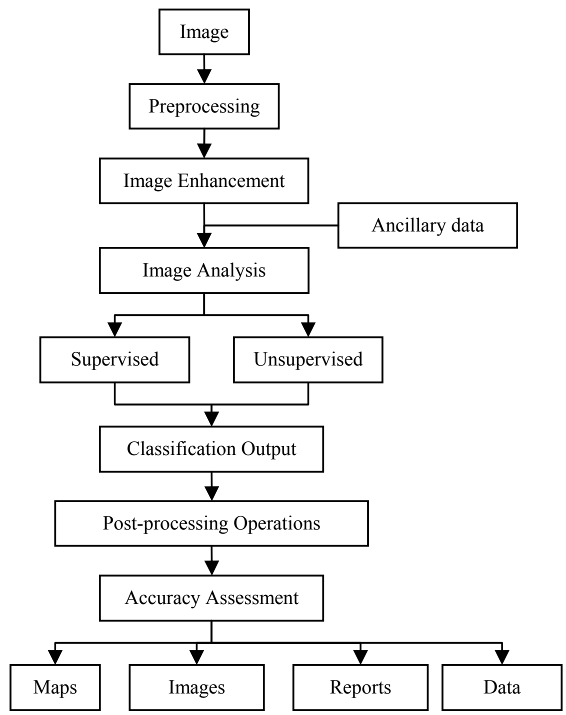


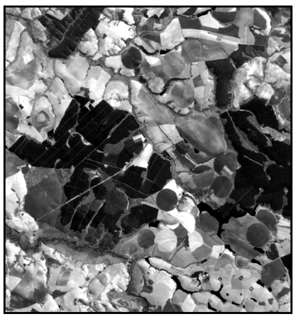
Figure 5 - Fundamental steps in remote sensing image processing .

A. *Image Registration*

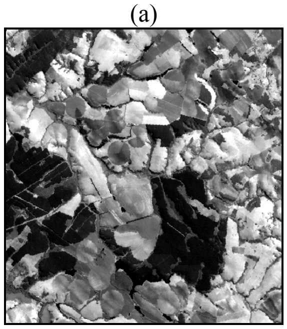
Registration is the process which makes the pixels in two images precisely coincide to the same points on the ground. The coordinates *(x,y)* of the input image that will be registered are adjusted to the coordinate system of the reference image so that the grids be superimposed. Fig. 6 illustrates the registration of two images Landsat-TM5 taken in different times.

Registration is a classical problem in several image processing applications where it is necessary to match two or more images of the same scene. Some of these applications are: integration of information taken from different sensors, analysis of changes in images taken at different times, object recognition, motion analysis, and weather prediction, the registration process is fundamental.

The registration operation basically involves the identification of many control points in the images. The traditional manual approach uses human assistance to identify the control points. As the manual control point identification may be time-consuming and tedious, automated techniques have been developed. Besides, the increasing number of satellite images has reinforced the need for automatic image registration methods.



(a)



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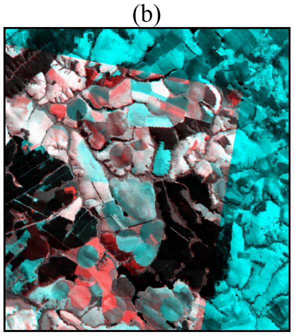


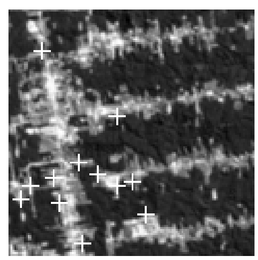
(c)

Figure 6 – Registration of multitemporal images: (a) input image, (b) reference image, and (c) input image is registered and superimposed on reference image in a color composition.

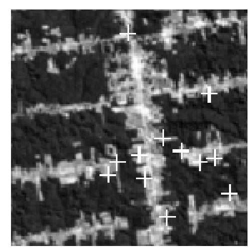
The general approach to image registration consists of the four following steps [10]:

- Feature identification: identifies a set of relevant features in a pair of images, such as edges, line intersections, region contours, regions textures, etc.
- Feature matching: establishes correspondence between the identified features. Thus, each feature in the input image must be matched to its corresponding feature in the reference image. Each feature is identified with a pixel location in the image. The corresponding points are usually referred to as control points (Fig. 7)
- Spatial transformation: determines the mapping function that matches all the points in the image using information about the control points obtained in the previous step.
- Interpolation: resamples the image using interpolation function to bring it into alignment with the reference image.

In general, registration methods differ from each other in the sense that they can combine different techniques for feature identification, feature matching, and interpolation functions. The most difficult step in image registration is obtaining the correspondence between the two sets of features. This task is crucial to the accuracy of image registration and much effort has been spent in the development of efficient feature matching techniques. Given the matches, the task of computing the appropriate mapping functions does not involve much difficulty. The interpolation process is also quite standard.



(a)



(b)

Figure 7 - Registering images of Amazon region, Landsat-TM5: (a) and (b) show control points (marked with crosses) superimposed on reference (07/06/1992) and input (15/07/1994) images.

Several techniques for automatic image registration have been developed [10]-[28]. Since the performance of a methodology is dependent on specific application, sensor characteristics, and the nature and composition of the imaged area, it is unlikely that a single registration scheme will work satisfactorily for all different applications. Our experience has shown that it is very difficult to perform a successful registration operation of remote sensed images without human assistance due to the problems such as the presence of clouds, different time acquisition and sensor characteristics. Consequently, information provided by the user can really help in the image processing.

Some commercial systems such as ENVI [29] have put some efforts on the development of semi-automatic registration tools to facilitate the whole process. Furthermore, the Instituto Nacional de Pesquisas Espacias (INPE) in cooperation with the Vision Lab at UCSB (University of California, Santa Barbara) developed an automatic system for image registration and mosaic which integrates many tools and information provided by the user to assist on the registration operation.

The registration system developed by INPE and UCSB is a full-featured application intended for operational use by beginners as well as by advanced users. The system contains toolboxes that increase the registration strength using the user's knowledge. In addition, there is a preprocessing module that can change the image resolution, select a specific band, enhance histogram, etc. The control point extraction can be done within small windows in the images instead of using the whole image. This is very useful in cases of dense cloudiness, multi-temporal ocean shots, images with small overlapping areas, etc. Furthermore, the set of control points may be edited in a powerful embedded editor or exported to external applications. A complete description of this system is provided in [14], [15]. This system can be freely downloaded [30].

Recently, this registration algorithm has been implemented using the TerraLib library. TerraLib is a GIS classes and functions library, available from the Internet as open source, allowing a collaborative environment and its use for the development of multiple GIS tools [31], [32].

B. *Image Fusion*

In remote sensing applications, the increasing availability of digital images in a variety of spatial resolution, and spectral bands provides strong motivations to combine images with complementary information to obtain hybrid products of greater quality. In order to accomplish this task, image fusion has been employed [33], [34].

Due to the physical constraint of a tradeoff between spatial and spectral resolution in remote sensing imagery, spatial enhancement of poor-resolution multispectral (MS) data is desirable. Multispectral image may exhibit limited spatial resolution that may be inadequate to a specific identification tasks despite of its good spectral resolution. On the other hand, panchromatic band (Pan) with higher spatial resolution may be merged with the MS bands to enhance the spatial resolution of the MS image.

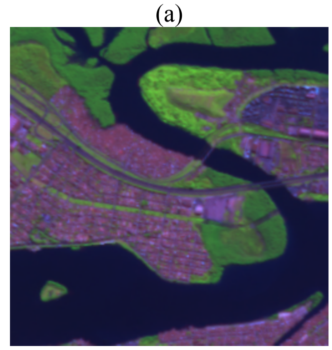
In this context, fusion process integrates the spatial detail of a high-resolution panchromatic image and the color information of a low-resolution multispectral (MS) image to produce a high-resolution MS image (hybrid product). The hybrid product should offer the highest possible spatial information content while still preserving good spectral information quality.

Many fusion methods such as those based on Principal Component Analysis (PCA), wavelet transform, arithmetic operations, IHS (intensity, hue, saturation) color model have been developed [33]-[59]. Despite the quite good results some limitations of the traditional fusion techniques such as the color distortion and the ability of the method to inject the details information in the hybrid product have been discussed in the literature.

Methods based on IHS transform are probably the most popular approaches used for enhancing the spatial resolution of multispectral images with panchromatic images [40]. The usual steps involved in this approach are as follows [1]:

1. Register the low resolution multispectral images to the same size as the panchromatic image
2. Transform the R,G and B bands of the multispectral image into IHS components
3. Modify the panchromatic image with respect to the multispectral image. This is usually performed by Histogram Matching of the panchromatic image with Intensity component of the multispectral images as reference
4. Replace the intensity component by the panchromatic image and perform inverse transformation to obtain a high resolution multispectral image.

(a)



(b)

(c)

Figure 8. Merging SPOT images. (a) Panchromatic image, (b) multispectral image R3G2B1, and (c) fused image obtained by IHS fusion method.

The fusion method based on PCA is also very simple [4], [44]. PCA method generates uncorrelated images (PC1, PC2, …,PCn, where n is the number of multispectral bands given as input). As the PC1 component has information similar to a panchromatic band, in the fusion method based on PCA, it is replaced by the panchromatic band of higher spatial resolution than the multispectral images. Afterwards, the inverse PCA transformation is applied to obtain the images in the RGB color model.

More recently, new techniques have been proposed such as those that combines Wavelet Transform with HIS model and PCA transform to manage the color and details information distortion in the fused image [58], [59]. Most methods based on wavelet transform exploits the context dependency by thresholding the local correlation coefficient between the images to be merged, to avoid injection of spatial details that are not likely to occur in the high spatial image [49]-[57]. These techniques seem to reduce the color distortion problem and to keep the statistical parameters invariable. The principal drawback consists on the selection of parameters that make them more complex.

Some researchers have evaluated different image fusion methods [60]-[62] using image quality measures [63], [64]. Nikolakopoulos [61] compared the efficiency of six techniques for fusing SPOT5 data: HIS, Modified HIS, PCA, Pansharp, Wavelet and LMM (Local Mean Matching). He concluded that the best fusion methods are the LMM and Pansharp for SPOT-5 image fusion.

Indeed, there is not a unique method that is adequate for every data and application. The fusion quality often depends upon the user's experience and upon the data set being fused [61]. The assistance of an interpreter in the fusion process is fundamental to guarantee the good quality of the product. Most image processing systems such as ENVI [29], SPRING [65], [66] and ERDAS [67] have image fusion module.

The merging process becomes more difficult in cases where the ratio between the spatial resolutions of both images is greater than 4. Modified fusion methods have presented good results but their limitation is still the selection of adequate tradeoff parameters.

C. *Image Segmentation*

Image segmentation is a basic task in image analysis whereby the image is partitioned into meaningful regions whose points have nearly the same properties, e.g., grey levels, mean values or textural properties [1], [4], [68], [69].

The segmentation process is one of the first steps in the remote sensing image analysis: the image is partitioned into regions which best represent the relevant objects in the scene. Region attributes can be extracted and used for further analysis of the data. In the object-oriented analysis, the quality of classification is directly affected by segmentation quality.

Segmentation methods are basically based on two approaches: (1) dividing up the image into a number of homogeneous regions, each having a unique label, (2) determining boundaries between homogeneous regions of different properties. These techniques are known as region growing and edge detection, respectively. Hybrid segmentation methods are obtained when both strategies are combined to generate the final result. Methods based on region growing approaches always provide closed contour regions, which is very simple and effective in many remote sensing applications. Various segmentation methods have been proposed and studied in the literature [67]-[88].

Most geographical information and image processing systems such as ENVI [29], SPRING [65], [66], ERDAS [67], Definiens [89] have efficient segmentation algorithms. Meinel and Neubert [70] compared some segmentation algorithms and algorithm based on region growing implemented in the system SPRING showed good overall results.

In general, the segmentation results are highly influenced by subjectivity because the user selects the segmentation parameters by the trial-and-error method. This way, the integration of instruments for evaluation of segmentation quality is very desirable [90]. Besides, the use of other attributes such as texture information for segmentation and combinations of region-based with algorithms of feature extraction, edge-oriented or model-based segmentation should be aspired for the improvement of segmentation quality [84].

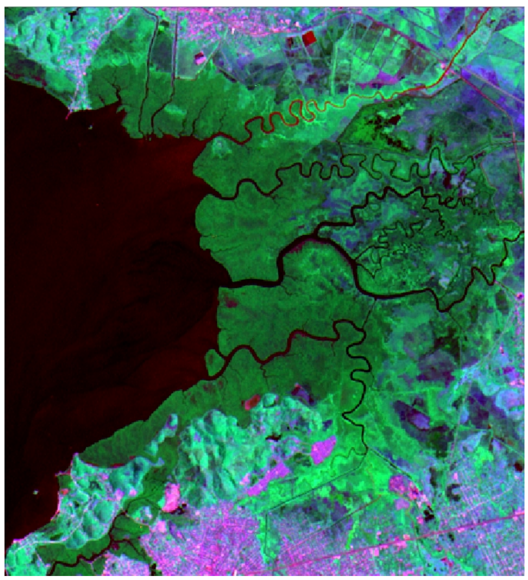
Differently, Korting et al. [85] proposed a method that uses results of a previous over-segmented image to generate regular shapes, i.e. rectangles and circles, by analyzing the connections in a weighted Region Adjacency Graph. Fig. 8 illustrates the objects contours obtained by region growing algorithm and refined by the re-segmentation algorithm proposed by [85].

Figure 9 - Contours of urban objects superimposed on image obtained by using region growing algorithm and re-segmentation algorithm proposed by [85].

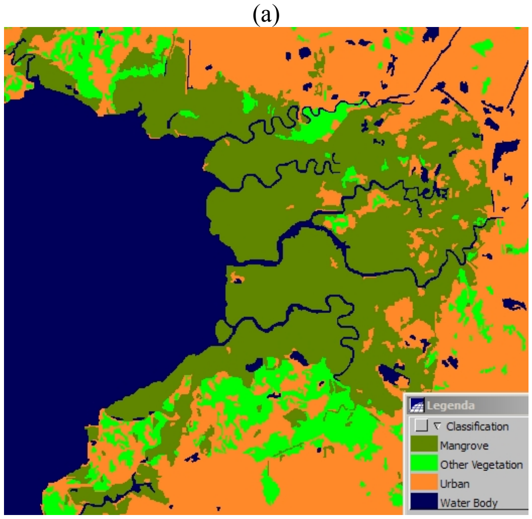
D. *Image Classification*

Image classification is the process used to produce thematic maps from remote sensing imagery. A thematic map represents the earth surface objects (soil, vegetation, roof, road, buildings), and its construction implies that the themes or categories selected for the map are distinguishable in the image. Many factors can difficult this task, including topography, shadowing, atmospheric effect, similar spectral signature, and others. In order to facilitate the discrimination among classes, regions obtained in the segmentation process are described by attributes (spectral, geometric, texture) that attempt to describe the objects of interest in the image.

The most used classification methods are supervised and they involve the following steps: feature extraction, training and labeling processes. The first step consists in transforming the multispectral image to a feature image to reduce the data dimensionality and improve the data interpretability. This processing phase is optional and comprises techniques such as HIS transformation, Principal Components Analysis, Linear Mixture Model, and multispectral ratios [1]-[4].



(a)



(b)

Figure 10 - Thematic map obtained from a Landsat-5 TM image: (a) Composition R3G4B5 of São Gonçalo municipality, RJ, Brasil, (b) Unsupervised classification based on Mahalanobis distance) [3].

In the training phase, a set of training samples in the image is selected to characterize each class. Training samples train the classifier to recognize the classes and are used to determine the "rules" which allow assignment of a class label to each pixel in the image. The labeling process consists in associating label for each pixel or region. Classification methods, presented in. Fig. 10, show an example of thematic map generated from multispectral image of TM sensor on board Landsat-5 satellite.

Different classification algorithms are available in the literature [1]-[4] and they are applied in accord to the type of data and application. Nowadays, the availability of high-resolution images has increased the number of researches on urban land use and earth cover classification. In most applications, pixel-per-pixel classifiers are not suitable since they can basically only handle spectral information [91]-[94]. An alternative to this shortcoming is to incorporate specialist knowledge or other types of attributes that are relevant to the classification process, such as region shape, size, texture information, and so on [95]-[98].

On the other hand, object oriented analysis offers effective tools to represent the knowledge of the scene. Therefore, knowledge-based image interpretation systems arise as an effective tool for image interpretation. In this approach, human expert's knowledge is organized in a knowledge base to be used as an input of automated interpretation processes, thus enhancing performance and accuracy, and reducing at the same time the subjectivity in the interpretation process [99]-[105]. Systems such a Definiens [89], ENVI- FX [29], and, more recently, InterImage [106], [107] have incorporated useful tools to help in the object-oriented classification.

In this context, Korting et al. [108], [109] have been developing a image mining tool, named GeoDMA, that is able to extract several features, from spatial to statistical and spectral attributes, performing the complete data mining process, including attributes selection, training, classification, visualization and validation to improve the classification task.

The thematic map (rater format) can be converted to the vector format using the raster to vector conversion operation. This step is essential in integrating the map into a digital spatial data base [110-112].

IV. Case Study: Urban Area

Intra-urban land cover classification of high spatial resolution images provides a useful set of information for urban management and planning [93]. With this type of data, it is possible to generate information for many applications, such as analysis of urban micro-climate and urban greening maps amongst others. The usage of automatic methods to classify high spatial resolution images faces the challenge of processing images with wide intra- and inter-classes spectral variability.

This section presents a case study for intra-urban land cover classification of QuickBird imagery for the city of São José dos Campos – SP, southeast of Brazil, based on Pinho's works [91], [101], [105]. The total and urban areas of the São

José dos Campos municipality, SP, Brasil, cover about 1,099.60 and 298.99 squared kilometers, respectively. The selected region is in the southern part of the urban area and contains a great variety of intra-urban land cover classes. Figure 11 shows the location and study area of São José dos Campos.

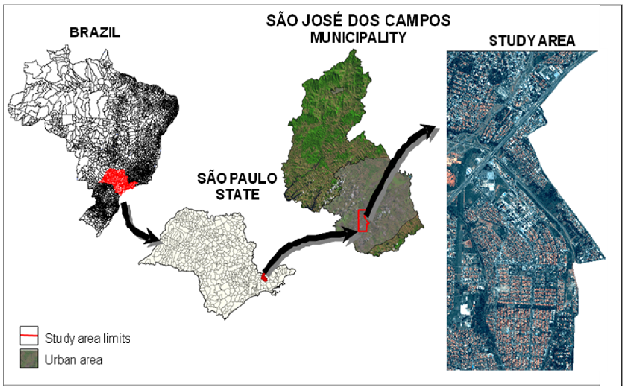


Figure 11 - Thematic map obtained from a Landsat-5 TM image.

The image used in this work is from the Quickbird (QB) satellite, launched on October 18, 2001. This satellite is sun-synchronous, orbits at an altitude of 450 km, with a 93.5-minute orbit time, crosses the equator at 10:30 am (local time) in its descending orbit, and its orbit inclination is 97.2 degrees.

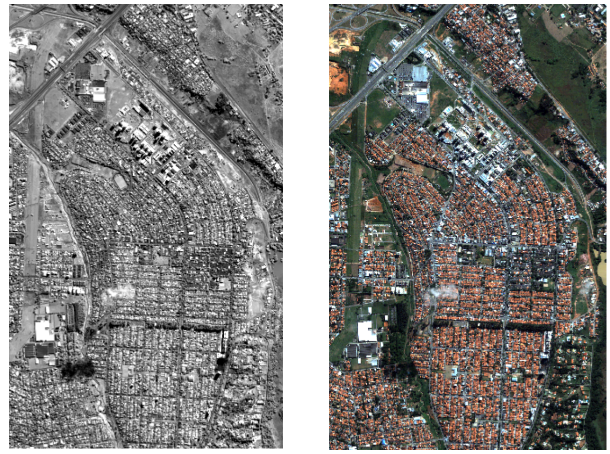
The QB scene (Ortho-ready Standard 2A) consists of: a panchromatic image (450-900 nm) and 0.6-meter spatial resolution; and a multispectral image with 2.4-meter spatial resolution, with 4 components: blue (450-520 nm), green (520-600 nm), red (630-690 nm), and infrared (760-900 nm). The images acquired on May 17, 2004 have an off-nadir incidence angle of 7.0^{o} and a radiometric resolution of 16 bits. Figures 12a and 12b show the panchromatic and multispectral images, respectively.

Following, we will present the processing phases carried out in this study.

A. Fusion

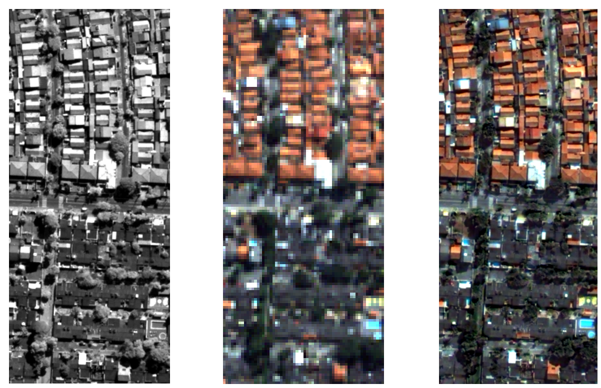
Pinho [101] used the fusion method based on Principal Components Analysis since it has shown good results in urban analysis with high resolution images [113]. The processing resulted in four images with spectral information similar to those of the original bands (blue, green, red and infrared) and spatial resolution equal to that of panchromatic image (0.6-meter).

The transformation is performed by a linear combination of the input images. Considering that the first principal component (PC1) is replaced by the panchromatic image in the PCA fusion method, the histograms of PC1 and panchromatic images are matched to obtain a good fusion. This implies in adjusting their mean and standard deviation values so that they be equal. Figures 13a, 13b, and 13c show a small region of the panchromatic image, multispectral image, and fused image, respectively.



(a) (b)

Figure 12 - Quickbird satellite scene acquired on May 17th 2004: (a) panchromatic image, with 0.6-meter spatial resolution, and (b) multispectral image, with 2.4-meter resolution, displayed using band 3 in red, band 2 in green and band 1 in blue.



(a) (b) (c)

Figure 13 - A small region of the image used in this study: (a) panchromatic image with 0.6-meter spatial resolution, (b) multispectral image with 2.4-meter resolution, and (c) fused image with 0.6-meter spatial resolution.

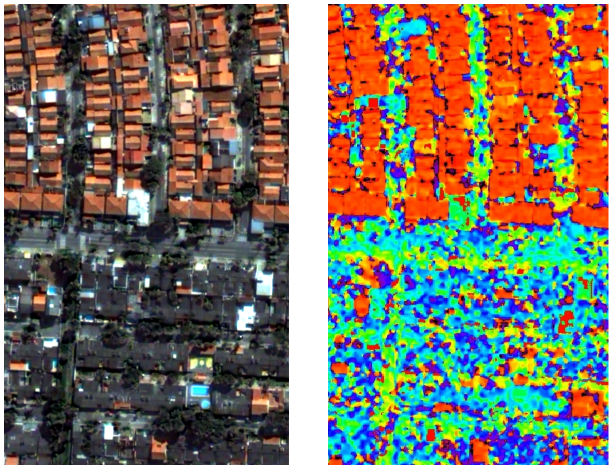
B. IHS Transformation

Types of land cover are discriminated by human visual system using the color composition in the visible electromagnetic spectrum [4]. In order to facilitate the use of user knowledge in the image interpretation process, IHS transformation can be used to create a new set of images named hue (H), intensity (I) and saturation (S).

In this experiment, the images Hue, intensity and saturation were obtained from the original bands, band 1 (450-520 nm), band 2 (520-600 nm), band 3 (630-690 nm). Band 4 (760-900 nm) was not used. Figures 13a and 13b display the color fused image (R3G2B1) used as input image and the component Hue obtained in the IHS transformation, respectively.

C. Multi-resolution segmentation

The approach selected for segmentation is based on region growing, where neighbor regions are grouped in an iterative process based on similarity. In addition, a minimum size criterion is used to avoid regions that are smaller than the targets of interest.



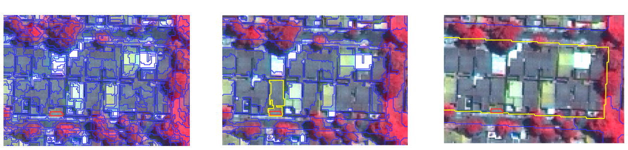
(a) (b)

Figure 14 - IHS transformation (a) color input image R3G2B1, and (b) component Hue.

In a multi-resolution segmentation, the similarity measure depends on scale since segmentation parameters are weighted by the objects size. Therefore, here the user defines four segmentation parameters: scale, weight for each spectral band, weight for color and shape, and weight for smoothness and compactness.

In this case, four levels of segmentation were created. Level I, with the smallest objects, separates objects based on land cover classes; level II differentiates vegetation and non-vegetation areas; level III defines objects as blocks and streets; and level IV defines objects as neighborhoods. Levels III and IV objects coincide with the city blocks and neighborhoods since a vector map with these boundaries were used in the segmentation procedure. In addition, levels I and II objects are constrained by the boundaries of levels III and IV. Fig. 15 shows a segmented region in levels I, II and III.

The visual analysis of levels I and II segmentation indicates that level II separates better the land cover classes than level I. This is due to level I segmentation parameters lead to over-segmentation. However, for classification, level I was important since level II objects eliminates boundaries of some relevant objects.



(a) (b) (c)

Figure 15 - Segmented region: (a) level I, (b) level II, and (c) level III. Note that objects with red boundary in level I is constrained by objects with yellow boundary in the level II and III.

D. Decision Tree building

The intra-urban land cover classification method used here is based on a decision tree, where the classifier labels objects accordingly to the rules described by the tree. To define the decision tree, classes of interest were defined based on visual interpretation to define interpretation keys. These keys helped the expert to create the tree.

Different types of objects such as roofs, pavements and vegetation were identified using the interpretation keys. The attributes used to characterize the classes were organized based on color, form, context, texture, size and location information.

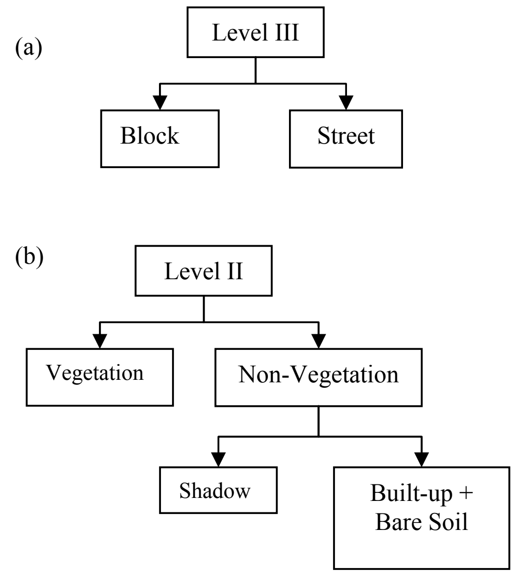


Figure 16 – Decision tree of levels: (a) II and (b) III.

The following classes were selected for classification: intense brightness objects (pale concrete, pale asbestos roofs and very bright metallic roof), trees, grass, shadows, asphalt, bare soil, ceramic roofs, dark concrete, dark asbestos roofs, medium tone concrete, medium tone asbestos roofs, metallic roofs, and swimming-pools.

The tree construction started from classes that are easier to be distinguished from others to the hardest ones. The best set of attributes to discriminate the classes was defined from a training set.

For each segmentation level one decision tree was created. The level IV was only used to aggregate land cover information by neighborhoods. Level III was used to differentiate blocks of streets. Vegetation, shadow, and built-up/bare soil classes were extracted from level II. Fig. 16 shows the decision tree of levels II and III.

The decision tree of level I (Fig. 17) is more complex than the previous ones and was obtained after various tests and modifications.

E. Classification Result

Classification was carried out using the previous decision trees and the attributes selected in the training phase. The following attributes were selected: brightness, hue channel mean, means of bands, belonging to super-object Block, maximum value in band 1, NDVI (Vegetation Index), ratio between bands 3 and 1, ratio between band 2 and the mean of all others, and difference mean for band 1. Fig. 18 shows the original multispectral image and the resultant classification.

The visual analysis of the classification indicates confusion between Ceramic Roof and Bare Soil classes while other classes are fairly well separated. Fig. 19 illustrates the confusion between these classes in a small region.

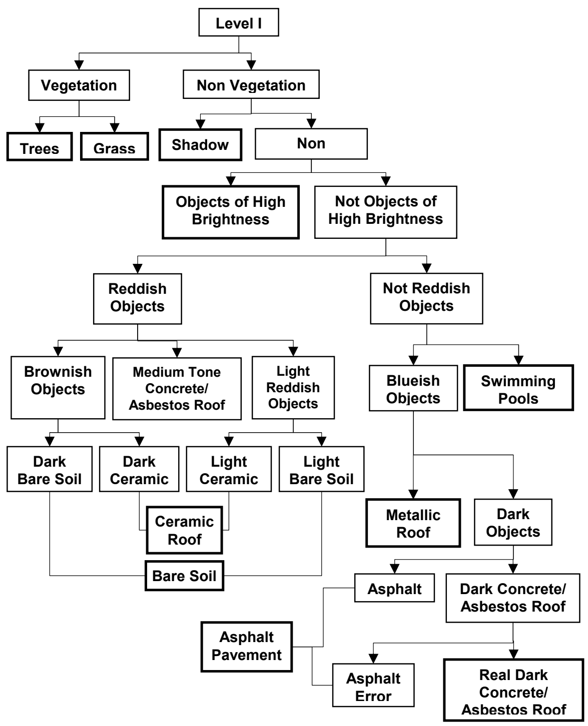


Figure 17 – Decision tree in the level I.

Quantitative classification accuracy assessment using error matrix points out a good classification with Kappa value of 0.57. A per class Kappa indicates lower values for Ceramic Roof and Bare Soil classes as expected from the visual analysis.

V. Conclusion

This paper presented a brief review about the general procedure employed to solve a remote sensing application using image processing techniques. A case study based on an urban application is provided to show an example of remote sensing application. Attention has been focused on principal image processing techniques with the hope that the information provided here would enable an interpreter or scientist to conduct research on remote sensing applications.

(a)

(b)

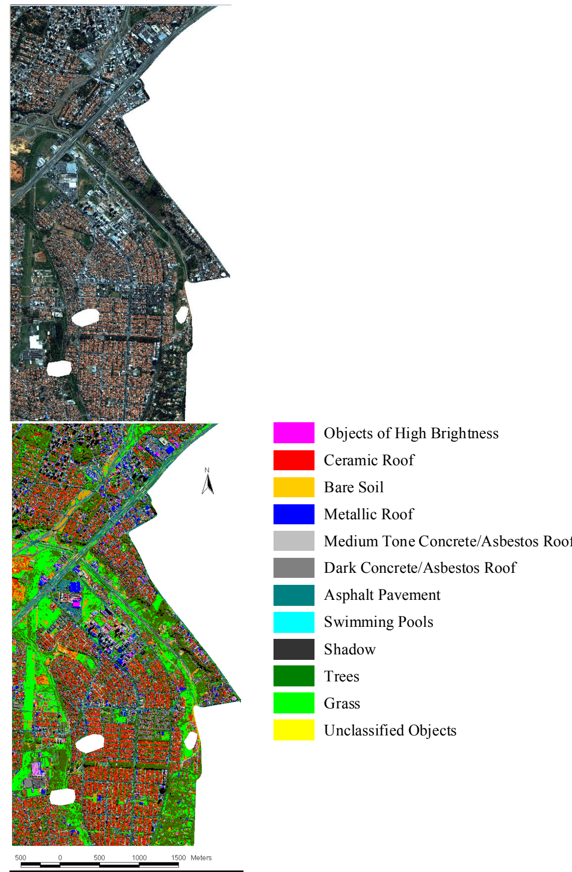


Figure 18 – Resultant classification (a) original color image and (b) thematic map.

(a)

(b)

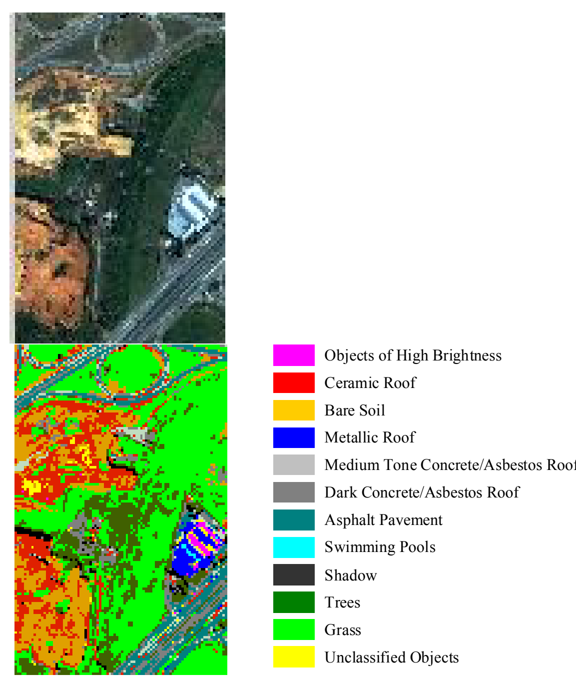


Figure 19 - Portion of the case study region (a) true color image and (b) classification result where there is confusion between Ceramic Roof and Bare Soil classes.

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