# OBJECT RECOGNITION USING SPHERICAL HARMONICS SHAPE DESCRIPTOR IN HYPERSPECTRAL IMAGERY

by

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Abstract of THESIS OR DISSERTATION Presented to the Graduate
School of the University of Puerto Rico in Partial Fulfillment of the
Requirements for the Degree of Master of Science Abstract

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Object recognition in hyperspectral and multispectral imagery has been studied in the last decade. The different approaches to recognition over hyperspectral images are based on spectral behavior, ignoring the shape behavior. On the other hand in multispectral, RGB and gray scale images the approaches are many; mainly considering the shape of the object, but neither of them considering the spectral behavior. In this research, our focus is to develop an algorithm that recognize a man-made objects such cars, buildings, etc using their shape and corresponding spectral information, therefore a fusion of these two sets of information gives is exploited here. The algorithm starts by segmenting the object, to isolate it from the background and other objects, then determining its geometric center, so as to extract its boundary, the geometric center is important in order to extract the shape descriptor. For the shape descriptor we use spherical harmonics, this descriptor have been widely used as a powerful tool for shape recognition but has not been applied to hyperspectral imagery. Once we have the shape descriptor, the boundary of the object's shape is analyzed and used to

recognize it. The algorithm is tested using real hyperspectral images taken from HYDICE sensor, SOC 700 Hyperspectral camera and multispectral aerial images.

Resumen de TESIS O DISERTACIÓN Presentado a Escuela
Graduada de la Universidad de Puerto Rico como requisito de los
Requerimientos para el grado de MAGISTER EN CIENCIA

# RECONOCIMIENTO DE OBJECTOS USANDO ESFÉRICOS ARMÓNICOS COMO DESCRIPTORES DE FORMA EN IMÁGENES HYPERSPECTRALES

por

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2011

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El reconocimiento de objetos en imágenes multiespectrales e hiperespectrales ha sido un tópico estudiado en los últimos años. En el campo de imágenes hiperespectrales las aproximaciones presentadas ponderan la información del comportamiento espectral e ignoran la silueta de los objetos analizados. Mientras que en las imágenes multiespectrales, RGB y escala de grises existen numerosas aproximaciones donde la mayoría pondera el comportamiento de la silueta pero no toma en consideración información espectral que no se tiene a disposición. El enfoque del presente trabajo de investigación es desarrollar un algoritmo capaz de reconocer objetos construidos por el hombre como: casas, carros, etc. usando el comportamiento de la forma del objeto y su correspondiente información espectral, la fusión de estos dos conjuntos de datos nos ofrecerá mejores resultados de reconocimiento. Para este propósito se seguirá un conjunto de pasos estructurados. Segmentaremos la imagen de tal forma que aislemos al objeto de los otros objetos así como del fondo. Determinaremos el centro geométrico del objeto para extraer el borde del mismo. Una vez que tengamos

definido el centro geométrico calcularemos el descriptor de forma. El descriptor de forma utilizado será esféricos armónicos, este descriptor ha sido ampliamente utilizado en reconocimiento de imágenes, pero hasta el momento no ha sido aplicado a imágenes hiperespectrales. Con el descriptor como resultado compararemos los diferentes bordes de descriptores para finalmente arribar al reconocimiento del objeto. El algoritmo será evaluado con datos reales tomados por el sensor HYDICE, la cámara hiperespectral SOC 700 y además con imágenes aéreas RGB. Este algoritmo puede ser aplicado a diferentes campos como: seguridad, defensa, salud. Y representa un avance significativo en el campo de reconocimiento de objetos.

*To my parents who encourage me to pursue my dreams,*
*To my siblings who always believe in me...*

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Thanks to my parent’s God.

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## CHAPTER 1

# 1 Introduction

## 1.1 Motivation

Hyperspectral and multispectral imagery analysis has recently studied and used in different fields such as agriculture, archeology, biology, defense, etc. Its large amounts of data taken at narrow and contiguous spectral bands are attractive to different applications such as object recognition providing important information to discriminate better different objects or regions. They are very suitable for this purpose because they provide a vision of the entire forest and the individual tree as well (Schott., 2007), and we want to see the tree (object) and compare with the rest of the forest (other objects), to recognize it.

For recognizing objects we have to extract some patterns or descriptor associated to the object to identify it unequivocally. These patterns are features that share some common properties: shape, materials composition, spectral information, locations, etc. In previous works there are different approaches over gray scale and 2D images; in (A. Sajjanhar, 2005) is presented an approach to identify a 2D image using a 3D reconstruction of it, the descriptor used is spherical harmonic, in this approach the recognition process is invariant over rotational, translational and even scaling transformations. These kinds of transformations are the most common in the quotidian behavior of the objects. In 2004 was presented (Zhi-yong, Zhi-geng, & min, 2004) where spherical harmonic was also used to recognize gray level image more efficiently.

For 3D images there are different approaches, but considering the nature of the image the most powerful tool developed was spherical harmonic descriptor. Funkhouser (Thomas Funkhouser, 2003), Abdallah (A. Ben Abdallah, 2008) and Kazhdan (Michael Kazhdan, 2003) present approaches to recognition using spherical harmonic; while Abdallah (A. Ben Abdallah, 2008) used for medical purpose using scintigraphic data; Kazhdan (Michael Kazhdan, 2003) use the information of 3D object to recognition process invariant to rotational transformation. Funkhouser (Thomas Funkhouser, 2003) present a general approach to recognize 3D object and 2D object in a search engine using the shape behavior and being invariant to rotational, translational and magnification transformations.

In hyperspectral recognition, approaches take advantage of the spectral information, but omitted the shape behavior. In (Healey & Slater, 1999) an approach to recognize materials using the spectral behavior along the bands is presented. Borghys (Dirk Borghys, 2007) present an approach on reducing the classification ambiguities of man-made objects.

An important part of object recognition process is the shape descriptor; everything can be summarized and reduced through its descriptor. Selecting a good descriptor is not a small challenge; there are many descriptors in pattern recognition and computer vision sciences, such as invariant moments, measurements, texture information, etc. Some of recently researchers based their descriptor on spherical harmonic functions (A. Sajjanhar, 2005; A. Ben Abdallah, 2008; Michael Kazhdan, 2003; Thomas Funkhouser, 2003), according to them spherical harmonic are the most suitable descriptor which improve the identification of the object ignoring rotation, translation transformation as well scaling. Also it is important to note that in (Michael Kazhdan, 2003) is reported that comparing with Fourier descriptor method it could be consider spherical harmonics as a generalization of it, such good qualities convert spherical harmonic in to a better choice to capture the object pattern.

The present thesis is taken advantage of the robustness and invariance of spherical harmonics descriptor and also the spectral behavior of hyperspectral images. Considering these two datasets convert the present approach in a novel technique to recognize man-made object recognition. Man-made objects are considered as target because they have good qualities to extract boundaries. The most of man-made objects have smooth and continuous borders.

However spherical harmonic are a descriptor intrinsically associated to volumetric object analysis. The present thesis change the approach of spherical harmonic descriptor to two-dimensional object sensed in a hyperspectral image, and consider the spectral behavior as a third dimension even is this third component is not spatially third dimensional. The selection of spherical harmonic is because even the nature of third space this descriptor present a good qualities of transformations invariance such as rotation and translation.

The motivation of the present work is taken advantage of these good qualities of information, such as shape in a two-dimensional image and also in depth such as spectral information in a hyperspectral image. These two datasets are important and until now is not taken in consideration.

## 1.2 Objectives

### 1.2.1 General Objective

To develop an algorithm to identify man-made objects in multispectral/hyperspectral images.

### 1.2.2 Specific Objectives

- To utilize shape priors or shape descriptors for invariant object recognition.
- Carry out diverse experiments with different hyperspectral, RGB and multispectral images allowing evaluation of the performance of spherical harmonics methods.

## 1.3 Contribution of this work

The main contribution of this research is the application of Spherical harmonics widely used in computer graphics and tridimensional environment over hyperspectral imagery to recognize man-made objects in different background and under different transformations.

In (Thomas Funkhouser, 2003) is proposed spherical harmonic as a part of an algorithm which is part of a research engine developed to identify an object based on one singular object searched. In there is proposed a new methodology of search engine, where the shape description is only needed to find it. However they do not consider the material of the objects because they only work with the shapes.

In this work, our approach is fusion of these two important sets of information: material and shape. The information given by hyperspectral image gives the material composed in object; while the boundary border of the shape gives the behavior of the object silhouette. Finally a behavior of the boundary of the border of the descriptor along the bands is the best approach to determinate the object, and this is the novel techniques presented in this work.

## 1.4 Outline

Chapter two contains a background and literature review in which we describe the background theory of hyperspectral images, the spherical harmonic shape descriptors, and object recognition process. All of these topics are important for understanding and developing the proposed application. Other related works are also described.

Chapter three presents the methodology used to develop the application for object recognition in hyperspectral images. We explain step by step what the application does. Chapter four shows the recognition results using different input data set with different sensor information. Our algorithm was tested with RGB and Hyperspectral imagery. Finally, chapter five contains our conclusions and suggestions for future work.

# CHAPTER 2

# 2 Background and literature review

This chapter explains fundamental concepts, and the review of previous work related to this research topic. The concept of hyperspectral imagery is described, as well as Object recognition process, with a special focus on spherical harmonic descriptor.

## 2.1 Hyperspectral Image

Remote sensing science has been getting attention the last decades due to capacity of sensed objects' properties on the earth's surface using data acquired from aircraft and satellites. It is therefore an attempt to measure something at a distance, rather than in situ. Since there is not contact with the object of interest, it uses different ways to acquire data, optical, acoustical or microwave signals are some of them. In the present research we focus our interest over optical signals, point measurements or a profile along a flight path; it means two-dimensional spatial grid i.e. images (Schowengerdt, 2007).

To meet the needs of different data users, many remote-sensing systems have been developed offering a wide range of spatial, spectral, and temporal parameters. Some user needs repetitive coverage images more than high spatial resolution. Others as in our case prefer highest possible spatial resolution with repeat coverage only infrequently. Since spatial resolution is managed with the distance between sensor and object of interest, the spectral information can be classified according to panchromatic, RGB, multispectral and hyperspectral images.

The electromagnetic spectrum is an important concept which lets us understand the benefits and behavior of multi and hyperspectral imagery. Each photon of light has a wavelength determined by its energy level. Light and other forms of electromagnetic radiation are commonly described in terms of their wavelengths. For example, visible light has wavelengths between 0.4 and 0.7 microns, while radio waves have wavelengths greater than about 30 cm (Figure 2-1)

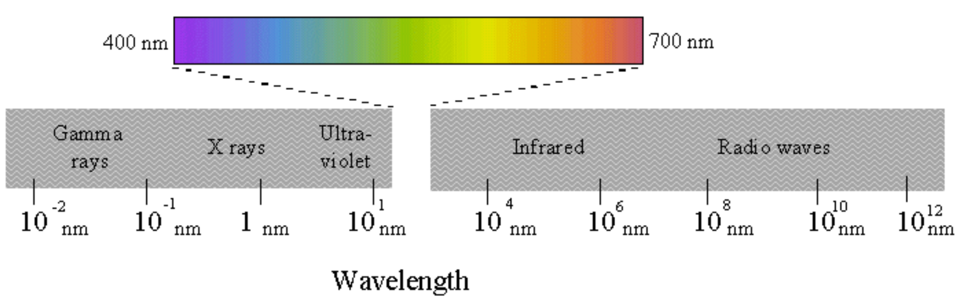



*Figure 2-1: The electromagnetic spectrum.* **(Smith, 2006)**

Reflectance is the percentage of light hitting a material that is then reflected by that material (as opposed to being absorbed or transmitted). A reflectance spectrum shows the reflectance of a material measured across a range of wavelengths. Some materials will reflect certain wavelengths of light, while other materials will absorb the same wavelengths. These patterns of reflectance and absorption across wavelengths can uniquely identify certain materials. As we have more details about the behavior of the materials in each spectrum we can analyze the images better (Figure 2-2).

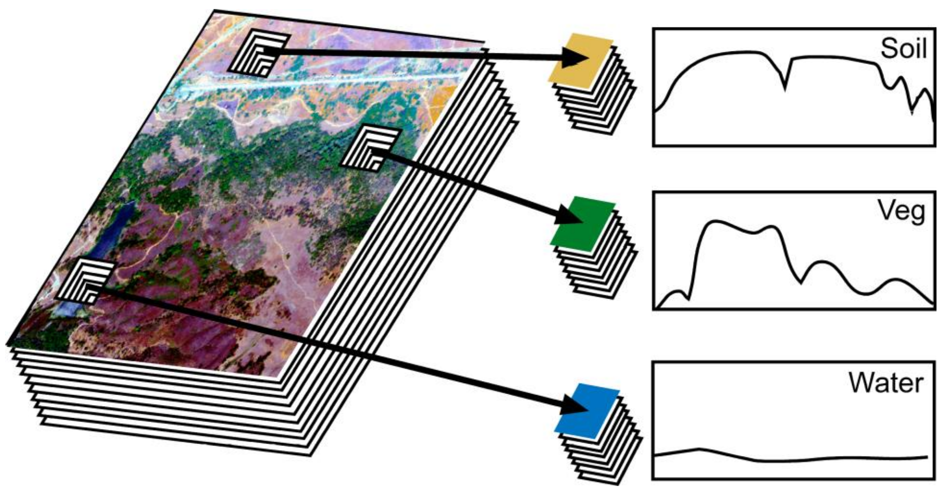



*Figure 2-2: Multi and hyperspectral Imagery.* **(Smith, 2006)**

One of the advantages of hyperspectral image is the measurement of information at many narrow, closely spaced wavelength bands, so that the resulting spectra appear to be continuous curves. When a spectrometer is used in an imaging sensor, the resulting images record a reflectance spectrum for each pixel in the images.

## 2.2 Object Recognition

Humans recognize a multitude of objects in images with little effort, despite the fact that the image of the objects may vary somewhat in different viewpoints, in many different sizes, scale or even when they are translated or rotated. Computer vision is limited in trying to simulate this cognitive human process to achieve object recognition using different tools and algorithms, but still does not achieve human accuracy (Figure 2-3) (Owens).

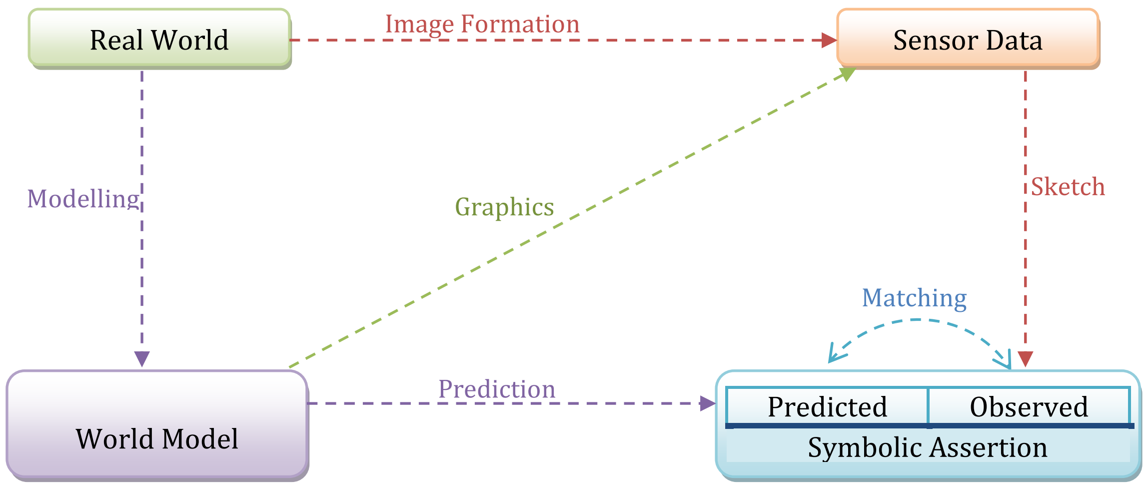



*Figure 2-3: From image capture of the real world to object recognition*

The problem in object recognition is to determine which, if any, of a given set of objects appear in a given image or image sequence. Thus object recognition is a problem of *matching* models from a database with representations of those models extracted from the image data. Of course, the *representation (description)* of the object model is extremely important. Clearly, it is impossible to keep a database that has examples of every view of an object under every possible condition.

In general there are two stages to any recognition system. The first is the *acquisition* stage, where a model library is constructed from certain *descriptions* of the objects. The second is *recognition*, where the system is presented with a perspective image and determines the location and identity of any objet from a library of objects (Owens).

Going through we can expand these two stages into four, adding the segmentation and representation stages. If we consider the construction of a database with some object models, first we have to segment the object to isolate from background and other objects, and second we have to determine or choose a good representation of the object to help us in the process of identification. Figure 2-4 illustrates the process of object recognition.

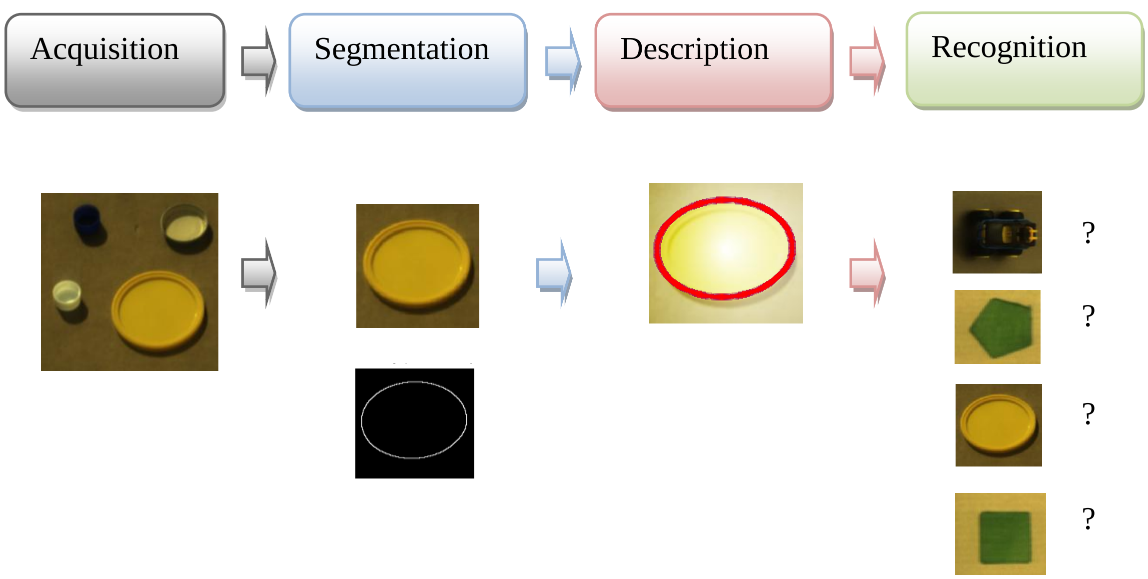



*Figure 2-4: Object Recognition process*

### 2.2.1 Acquisition

In this first stage the problem is concerned about capturing the information from the real world. The present research focus the acquisition part on spectral information sensed as was explained in Section 2.1.

### 2.2.2 Segmentation

Once we have the object in a digital form, we have to isolate it to extract the most important information about the object of interest.

The goal of segmentation is to divide an image into parts that corresponded to objects. Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried out depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated.

Segmentation of nontrivial images is one of the most difficult tasks in image processing. Segmentation accuracy determines the eventual success or failure of computerized analysis procedures. For this reason, considerable care should be taken to improve the probability of rugged segmentation.

Image Segmentation algorithms generally are based on one of two basic properties of intensity values: discontinuity and similarity. In the first category, the approach to partition an image based on abrupt changes in intensity, such as edges in an image. The principal approach in the second category is based on partitioning an image into regions that are similar according to a set of predefined criteria. Thresholding, region growing and region splitting and merging are examples of methods in this category (Gonzales & Woods, 2002).

It is not the scope of the present research just to extend segmentation stage, but we want to focus on the next stage: Description.

### 2.2.3 Description

In this stage the main problem is capture the essence of the object that can represent it unequivocally. In (Gonzales & Woods, 2002) describe this representation like an arrangement of *descriptors* called patterns. Pattern Recognition by machine involves techniques for assigning patterns to their respective classes automatically and with as little human intervention as possible.

Three common pattern arrangements used in practice are vectors (for quantitative descriptions) and strings and trees (for structural descriptions).

$$\boldsymbol{x} = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ x_n \end{bmatrix} \tag{2.1}$$

Where each component, $x_i$, represents the *i*th descriptor and n the total number of such descriptors associated with the pattern. The nature of the component of a pattern vector **x** depends on the approach used to describe the physical pattern itself.

Early work involved the extraction of three-dimensional models from stereo data to extract the descriptors or pattern arrangement, but more recent work has concentrated on recognizing objects from geometric invariant descriptors extracted from two-dimensional data. And the most recent work is related to spherical harmonics descriptor as the most powerful tool to extract a shape descriptor invariant under transformations like: rotation, translation, shift, etc.

#### *2.2.3.1 Spherical harmonic descriptor*

Just as the Fourier basis represents an important tool for evaluation of convolutions in a one- or two dimensional spaces, the spherical harmonic basis is a similar tool but defined on the surface of a sphere. Spherical harmonics have already been used in the field of computer graphics.

To arrive at spherical harmonic descriptor, we start describing orthogonal functions.

### *Orthogonal Functions*

Orthogonal functions are classes of functions $\{p_n(x)\}$ that obey an orthogonality relation over their domain [a;b] (Schönefeld, 2005):

$$\int_a^b w(x)p_n(x)p_m(x)\,dx \tag{2.2}$$

and

$$\int_a^b w(x)p_n(x)\overline{p_m(x)}\,dx \tag{2.3}$$

$w(x)$ is an arbitrary weighting function independent of *n* as well as *m*. With this property $p_n(x)$ is then called a *basis function*. The *basis functions* $p_n(x)$ are small pieces of information. Scaling and combining them produces either exactly the original function *f* (if an infinite series of basis functions is used or the function is band-limited) or a band-limited approximation $\tilde{f}$ of the source function (if only a finite number of basis functions is used while the source function also consists of signals of higher frequency than the threshold). Band-limiting means that frequencies higher than a certain threshold are removed and this is similar to a low-pass filter applied to the function before the harmonic expansion.

So everything needed to approximate a given function *f* arbitrarily accurate is to compute the coefficients $k_n$ describing how much each basis function $p_n$ is like *f* . This is done by integrating the product:

$$\int f(x)p_n(x)dx = k_n \tag{2.4}$$

over the full domain of $f$ . The aforementioned process is called projection or expansion. Its inverse process is defined as the linear combination of all basis functions scaled by their associated coefficients

$$f(x) = \sum_{n=0}^{\infty} k_n p_n \qquad or \qquad \tilde{f}(x) = \sum_{n=0}^{N} k_n p_n \tag{2.5}$$

***Spherical harmonic Descriptor***

Spherical harmonic descriptor is the result of applying the spherical harmonic function as a feature extraction method over the data acquired and segmented in the previous stages. In the literature (Thomas Funkhouser, 2003; Michael Kazhdan, 2003) spherical harmonic function are expressed as follows:

$$Y_m^n(\theta, \phi) = N_m^{|n|} P_m^{|n|}(Cos\ \theta) e^{im\phi} \tag{2.6}$$

This complete formal definition of the complex-valued spherical harmonic series has two arguments $m \in N_0$ and $-m \leq n \leq m$. $N_m^{|n|}$ is a normalization coefficient, while $P_m^{|n|}$ is the Legendre polynomial. Using Euler's formula the equation can be rewritten as:

$$Y_m^n(\theta,\phi) = N_m^{|n|} P_m^{|n|}(Cos\,\theta)(cos(m\phi) + i\,sin(m\phi)) \tag{2.7}$$

It becomes evident that, as described above the spherical harmonics are based on the associated Legendre polynomials for the $\theta$ and cosine functions for the $\phi$ dependence. $P_m^{|n|}$ is the associated Legendre polynomials and it is defined as:

$$P_m^{|n|} = (-1)^n (1-x^2)^{n/2} \frac{d^n}{dx^n} P_m \tag{2.8}$$

$$P_m = \frac{1}{2^m m!} [\frac{d^m}{dx^m}(x^2-1)^m] \tag{2.9}$$

For our purpose in Legendre Polynomials we use n that goes from 0 to m, i. e. n = 0,1,2,…, m.

Summarizing spherical harmonics functions are orthogonal functions that identify different information in different frequencies which help to extract a pattern of the boundary detected object. Since we know that orthogonal functions refers to a set of sine an cosine we can interpreter the Spherical harmonic like a generalization of the Generic Fourier descriptor, in (A. Sajjanhar, 2005) they showed a comparison between these descriptors.

A good descriptor is a vector or a set of vectors which describe in better way the object. The desirable properties are associated to quick computing, concise to store, and mainly invariant under transformations. Since an object in a quotidian life change the position, the angle, the illuminations and also the sensor which collect data change the position to take data. It is very important to describe the object that ignore these changes and concentrate in the characteristic unchangeable such as shape and materials

Spherical harmonic descriptor concentrate the power more than be quick to compute and concise to store. This descriptor is invariant under translational and rotational transformations. To be translational invariant the center of spherical coordinates has to be in the geometric center. Since spherical harmonic are applied to volumetric object and in our case our focus is over Hyperspectral image, the third dimension are considered the intensity along the bands, but this third dimension is not spatial, is in spectral range, and also depend of the other two-dimensional variables of X and Y, rows and columns of the image in the two-dimensional space.

For rotational invariance spherical harmonic has the property of not change the $L_2$ norm $\|Y_m^n(\theta,\phi)\|$ even if the function is rotated. It is define a rotation invariant signature for $Y_m^n(\theta,\phi)$ as a collection of scalars (Thomas Funkhouser, 2003).

### 2.2.4 Recognition

Decision-theoretic approaches to recognition are based on the use of *decision* (or discriminant) *functions*. Let $\mathbf{x} = (x_1, x_2, \dots, x_n)^T$ represent the *n*-dimensional pattern vector, as discussed in the previous stage. For *W* pattern class $\omega_1, \omega_2, \ldots, \omega_w$, the basic problem in decision-theoretic pattern recognition is to find W decision functions $d_1(\mathbf{x}), d_2(\mathbf{x}), \ldots, d_w(\mathbf{x})$ with the property that, if a pattern **x** belongs to class (object) $\omega_i$, then

$$d_i(x) > d_j(x) \qquad j = 1,2,\ldots.,W; j \neq i \tag{2.10}$$

In other words, an unknown pattern or object **x** is said to belong to the *i*th pattern class or known object if, upon substitution of **x** into all decision functions, $d_i(x)$ yields the largest numerical value. (Gonzales & Woods, 2002)

The *decision boundary* separating class $\omega_i$ from $\omega_j$ is given by values of x for which $d_i(x) = d_j(x)$ or, equivalently, by values of x for which

$$d_i(x) - d_j(x) = 0 \tag{2.11}$$

Common practice is to identify the decision boundary between two classes by the single function $d_{ij}(x) = d_i(x) – d_j(x) = 0$. Thus $d_{ij}(x) >0$ for patterns of class $\omega_i$ and $d_{ij}(x) < 0$ for pattern of class $\omega_j$.

Recognition techniques based on ***matching*** represent each class by a prototype patter vector. An unknown pattern is assigned to the class to which it is closest in terms of a predefined metric. The simplest approach is the minimum-distance classifier, which, as its name implies, computes the (Euclidean) distance between the unknown and each of the prototype vectors. It chooses the smallest distance to make a decision.

To understand how work minimum distance discriminate function, suppose that we define the prototype of each pattern class to be the mean vector of the patterns of that class:

$$\boldsymbol{m}_j = \frac{1}{N_j} \sum_{x \in w_j} x_j \quad j = 1, 2, \dots, W \tag{2.12}$$

Where $N_j$ is the number of pattern vectors from class $\omega_j$ and the summation is taken over these vectors. As before, W is the number of pattern classes. One way to determine the class membership of an unknown pattern vector **x** is to assign it to the class of its closest prototype, as noted previously. Using the Euclidean distance to determine closeness reduces the problem to computing the distance measures:

$$D_j(x) = \left\| x - m_j \right\| \; j = 1,2, \dots, W \tag{2.13}$$

Where a = $(a^T z)^{½}$ is the Euclidean norm. We then assign **x** to class $\omega_i$ if $D_i(\mathbf{x})$ is the smallest distance. That is, the smallest distance implies the best match in this formulation. (Gonzales & Woods, 2002).

Euclidean Distance is defined as follow:

$$d(r,s) = d(s,r) = \sqrt{(s_1 - r_1)^2 + (s_2 - r_2)^2 + \ldots + (s_b - r_b)^2} = \sqrt{\sum_{i=1}^{b} (s_i - r_i)^2} \qquad (2.14)$$

# CHAPTER 3

# 3 Methodology

## 3.1 Algorithm Description

The present research has the goal to detect objects subject to transformations such as rotation and translation in high resolution spectral imagery by utilizing spectral and spatial information. For this purpose Figure 3-1 illustrates the flow chart of the algorithm:

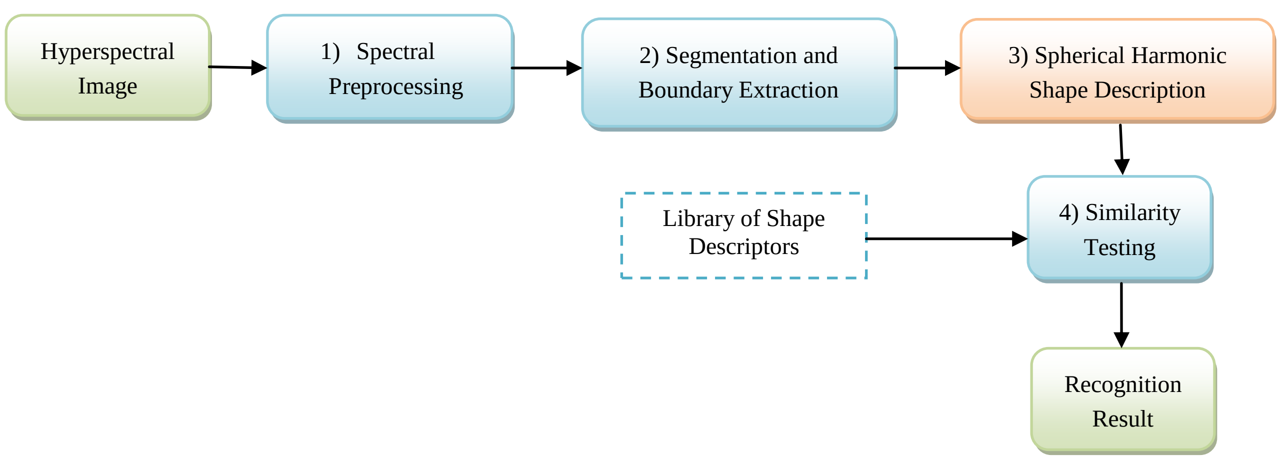



*Figure 3-1: Flow chart of the algorithm proposed*

The proposed algorithm recognizes different objects invariant to translation and rotation transformations. An object in an image can be defined region based or a shape based, which contains pixels located in such position inherent to the object, added to this in hyperspectral imagery the spectral behavior in different bands are also considered. All of this information must be evaluated to recognize the object. Each of algorithm steps contributes with the description extraction and added to our library. The recognition process starts when compare one object description to others description from library and find which is the best matching. An example is the follow flow chart described in Figure 3-2.

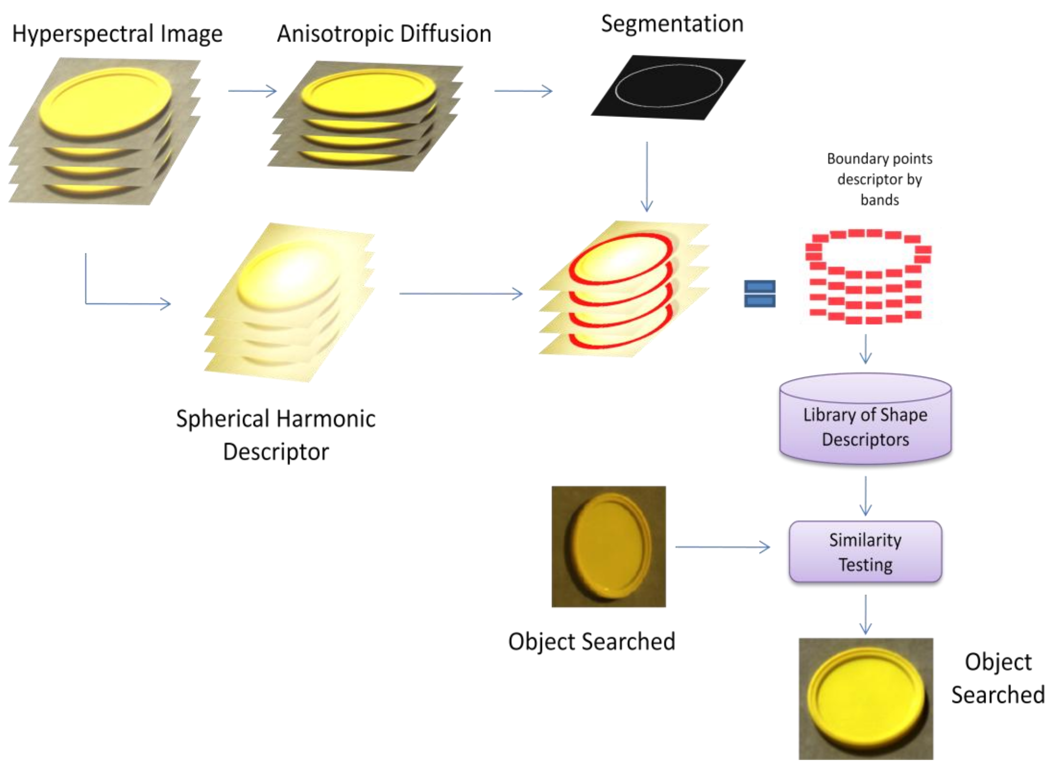



*Figure 3-2: Flow chart of recognition process*

### 3.1.1 Spectral Preprocessing

Based on the process described in (Julio M. Duarte-Carvajalino, 2007) we apply a preprocessing step to the image in order to enhance the edges. Anisotropic diffusion is the method utilized.

This step helps us to segment the object in the next step. With the edges enhanced we are not losing the spectral and spatial information, and we can determine easily the objects boundaries.

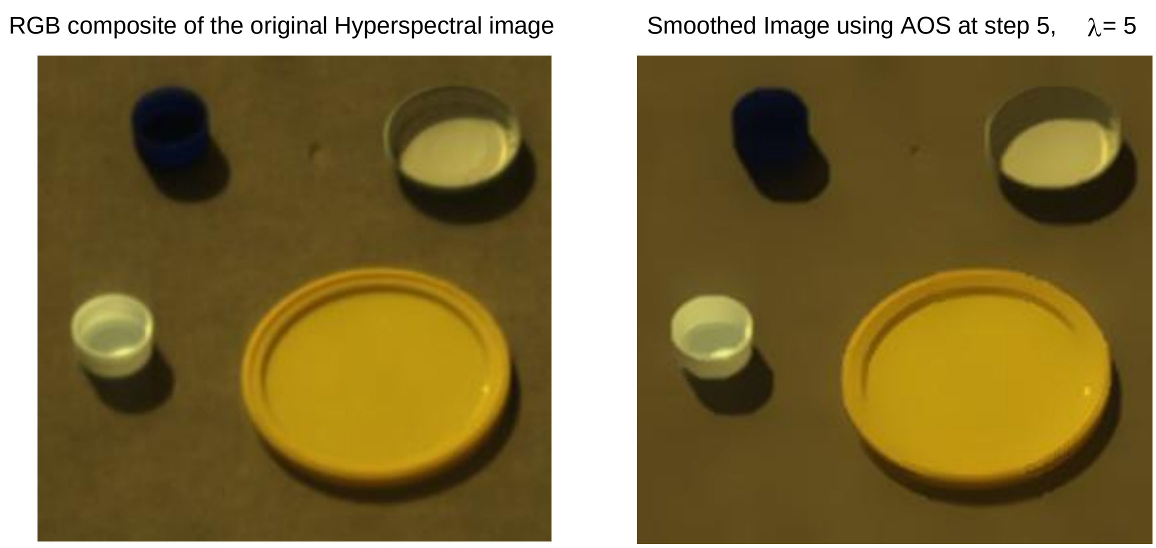



*Figure 3-3: Results of Anisotropic Diffusion*

### 3.1.2 Object segmentation and boundary extraction

Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. There are many different techniques of image segmentation depending on the type of image and the objectives. Particularly, for object segmentation, active contours have been used popularly to segment objects from background. This methodology is based upon the utilization of deformable contours which conform to various object shapes and motions.

Active contour is based on the idea of deforming the initial curve to the boundary of objects under some constraints from the image using techniques of curve evolution.

The basic idea of active contours is to start with initial boundary shapes represented in a form of closed curves. Then, they are iteratively modified by applying shrink/expansion operations according to certain image constraints. The shrink/expansion operations, called contour evolution, can be performed by the minimization of an energy function (Huaman De la Vega & Manian, 2010).

In order to apply active contour and graph-cuts we provide to the algorithm training pixels of the object (target), the shrink/expansion operations return the object boundary. Figure 3-4 shows the result of applying the boundary extraction to one single element in the image.

RGB Composite of the Original Hyperspectral Image

Active Contour with Graph-Cut boundary extraction

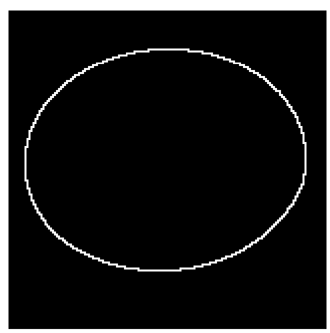


*Figure 3-4: Active Contour with Graph cut boundary extraction*

The spatial resolution of the image is important to extract the boundary, if the object is too small (big spatial resolution), extracting the boundary will be a huge challenge. For these situations we apply different boundary extraction methods which can be listed as:

- Edges methods: Canny, Sobel
- Bwboundaries from Matlab

For different objects in the same image, we have applied Canny or Sobel edge detection after preprocessing the image with anisotropic diffusion. Figure 3-5 and Figure 3-6 show the results of canny and sobel edge detection.

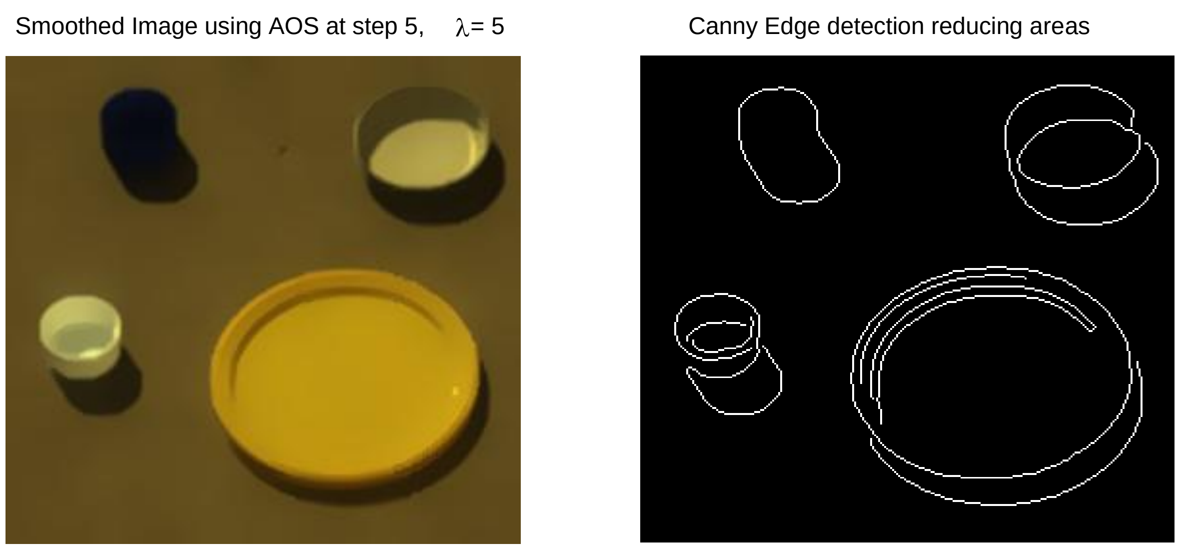



*Figure 3-5: Canny edge detection for Hyperspectral SOC 700 camera images*

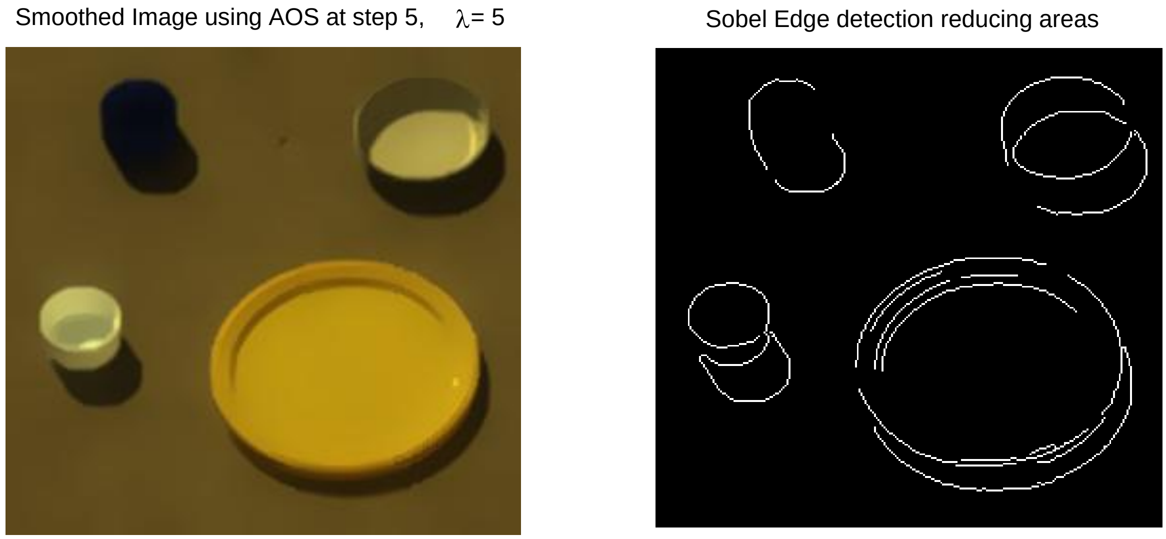



*Figure 3-6: Sobel edge detection for Hyperspectral SOC 700 camera images*

Our purpose is analyzing images sensed remotely. The problem as we said before is the spatial resolution in hyperspectral remote images, but in aerial imagery the spatial resolution are enough to extract objects boundaries. Figure 3-7 and Figure 3-8 show the results for Canny and Sobel edge detection.


*Figure 3-7: Canny Edge detection for Aerial Image*


*Figure 3-8: Sobel Edge detection for Aerial Image*

As we can see the results above cannot isolate the object by its total shape. So, we apply a little preprocessing using transformation and a specific boundary extraction function from Matlab called bwboundaries. Figure 3-9 shows the results for Hyperspectral SOC 700 images and Figure 3-10 shows for Aerial Image.

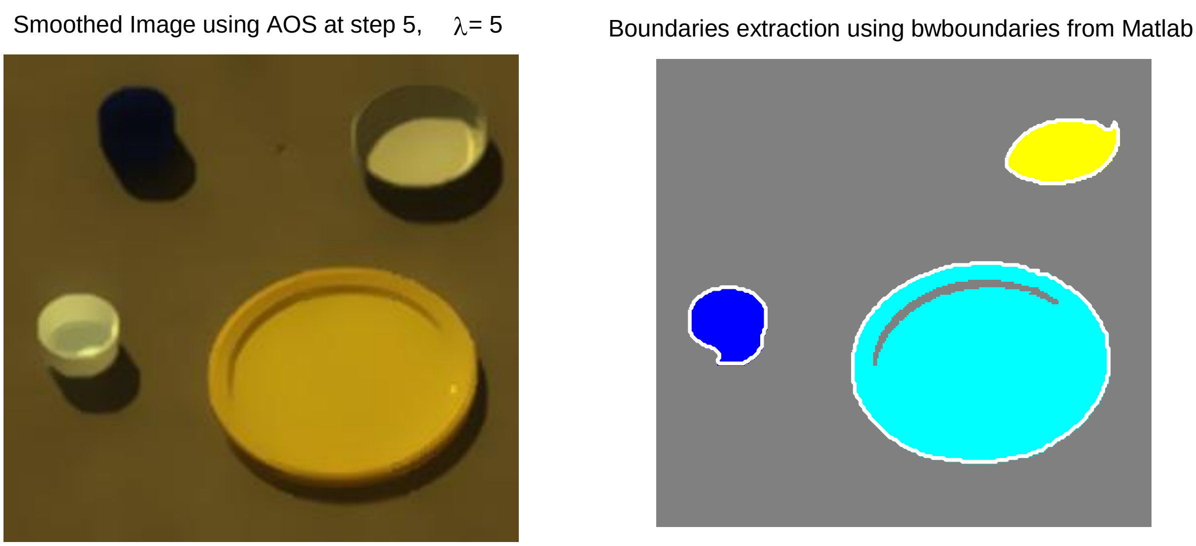



*Figure 3-9: Boundary extraction of Hyperspectral SOC 700 image*

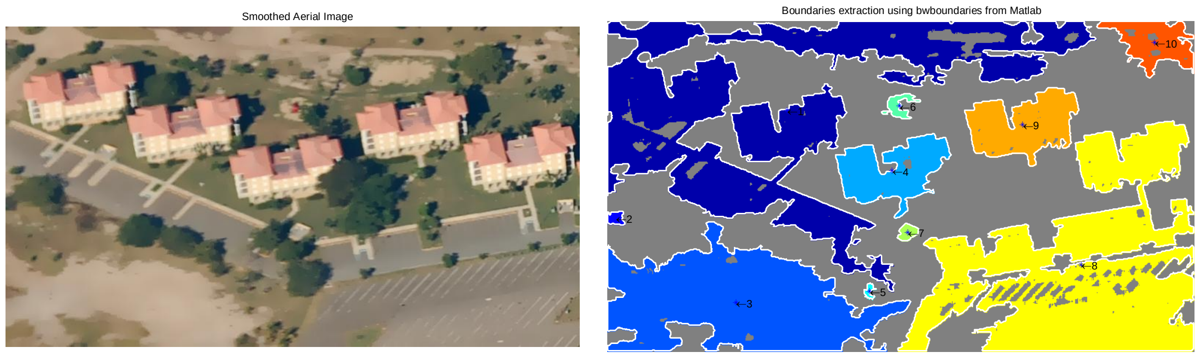
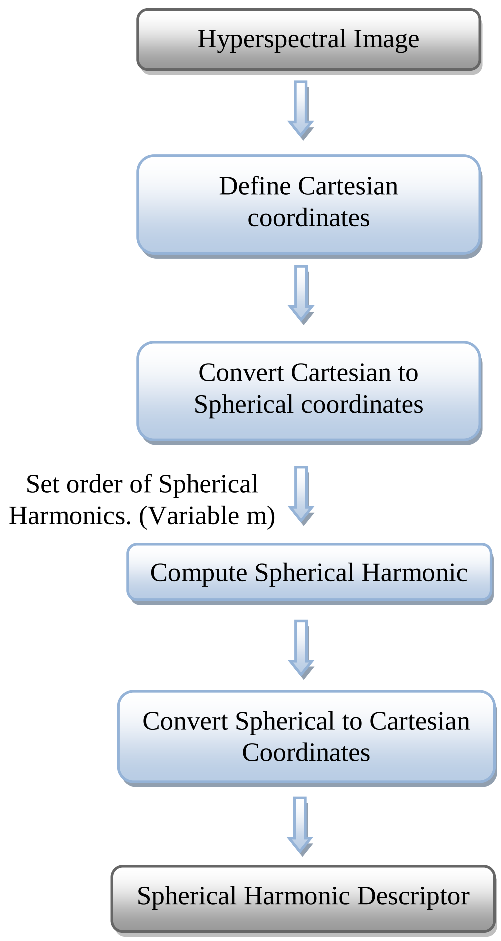


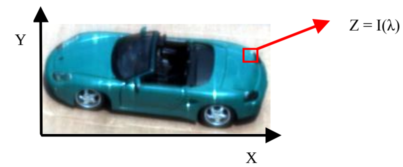

*Figure 3-10: Boundary extraction of Aerial Image*

### 3.1.3 Spherical harmonic shape description

Once the contour representation is obtained, the next step will be to compute invariant shape descriptors. To compute shape descriptor, we analyzed different literature to get the most powerful invariant shape descriptor. Spherical harmonic is the approach that fits our needs.

The boundary of the object previously extracted is used to determine the centroid of the object. It is important to set the centroid because it serves to set the axis of origin of the Cartesian plane. Starting with the basis that our multi-hyper spectral image is displayed in Cartesian plane, we have to convert first to spherical plane because spherical harmonics works in Spherical coordinates. Figure 3-11 illustrates the process of spherical harmonic descriptor extraction.




$$r = \sqrt{x^2 + y^2 + I(\lambda)^2}$$
$$\phi = \cot\left(\frac{y}{x}\right)$$
$$\theta = Sin^{-1}\left(\frac{\sqrt{x^2 + y^2}}{r}\right) = Cos^{-1}\left(\frac{I(\lambda)}{r}\right)$$

$$H = Y_m^n(\theta, \phi) = \sum_{m=1}^{M} \sum_{n=-m}^{m} N_m^{|n|} P_m^{|n|}(Cos\ \theta)(cos(m\phi) + i\ sin(m\phi))$$

$$x' = HCos\phi Sin\theta$$
$$y' = HSin\phi Sin\theta$$
$$I(\lambda)' = z' = HCos\theta$$

*Figure 3-11: Flow chart of Spherical harmonic extraction*

Creation of library of shape descriptors: The SOC-700 hyperspectral camera with 120 bands will be used to acquire images of different objects and their transformations. These images will be used to create a library of original shape descriptors. In addition to SOC-700 hyperspectral camera we collect data from different sensors like AVIRIS, and aerial images.

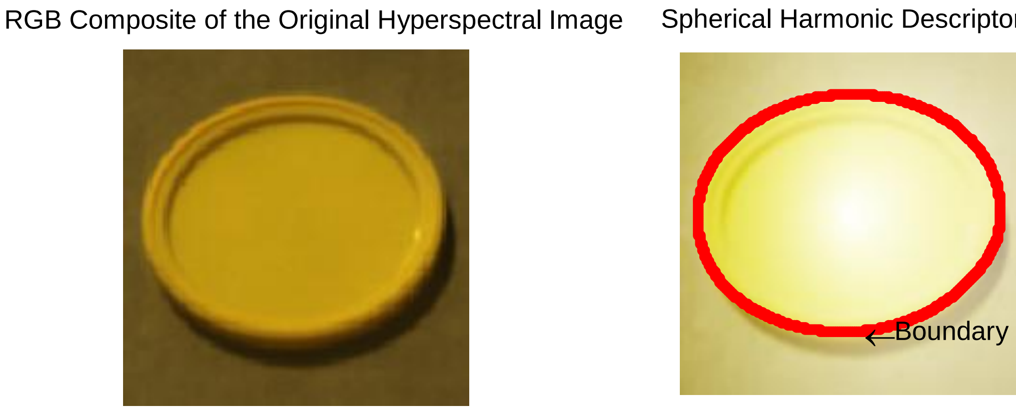



*Figure 3-12: Spherical Harmonic Descriptor for Hyperspectral SOC700 single object*

### 3.1.4 Recognition

There are different definitions that lead to a definition of similarity between a pair of model objects. These include vote-based criterion, object/feature similarity and object/hypothesis similarity. In this case, we will use a simple Euclidean distance based similarity metric for recognition. The distance between the descriptor for the transformed object and a library of descriptors will be computed. The transformed object will be recognized as the object with the smallest distance in the library.

We are going to compare the spherical descriptor of the objects boundaries. Each pixel around the boundary will be compared. For the group of distances between different points of the boundaries, we calculate the mean, and choose the minimum. The object with the minimum distance will be the object recognized.

# CHAPTER 4

# 4 Experimental Results

In this chapter we present the experimental results. They are carried out using RGB and Hyperspectral images.

RGB images are tested considering the benefits of its spatial resolution. All of them are taken by aircraft; our purpose is proof the efficiency of the algorithm for recognition of objects sensed remotely. Since as far as the sensor is more reduced is the size of the object (low spatial resolution) and hence, we have problems with the boundary extraction. In case of aerial imagery the spatial resolution is good that we could extract a defined boundary.

In case of Hyperspectral Image, we use a SOC 700 hyperspectral camera, whose spectral bands ranges over the visible spectrum. This camera has been used to prove the efficiency of the algorithm for object recognition with the same shape and different material, and object with the same material and different shape. We want to prove that the algorithm is strong enough to discriminate different shape of object with the same material. Also the result of this camera is strongly useful to determinate the boundary for object sensed remotely.

Also we use HYDICE sensor image, with a spatial resolution of 4m we face a problem with the boundary extraction. The low spatial resolution gives problems because mix materials and object, we could not identify small object such cars, even the buildings have problem with the diffused border. However when a object is such big that we can extract the boundary we can compare and determinate the best matching that visually can gives us good accuracy.

## 4.1 Software System Developed

In this chapter are presented two kinds of experiments. One is using an image with different objects in it and recognize one of the elements of the whole image compare with the others objects of the same image. And the second type of experiment compares one single image with a database collection of single images. These two kinds of experiment are explained in the following steps. Our algorithm is developed based in these two kind of approach, the software developed kind summarizes in the following steps for each kind of experiment.

Experiment type 1 – Many objects per image:

1. Apply to original image anisotropic diffusion to preserve the edge and smooth the rest of the image. Use 5 steps, lambda in 5, and gradient threshold in 0.012.
2. Convert diffused image obtained in previous step to binary image. In case of hyperspectral image consider just the RGB representations bands to convert to

gray scale and after that convert to binary using the function b2w of matlab with graytresh of gray image.

3. Define the center of coordinates in each object centroid using the boundaries extracted in previous step.
4. Extract the spherical harmonic descriptor using the process define in Section 3.1.3 over the original image for each object found. Using M=3 to extract the first 16 frequencies of spherical harmonic.
5. Save the respective boundaries points of the descriptor fusion of information of boundary obtained in step 2 and the descriptor obtained in step 4. For each point of the boundary extract the value in the descriptor data for each band. The final result if our final descriptor.
6. Compare one descriptor to others to find the best match. Use Euclidean distance.

Experiment type 2 – One object per image:

1. Apply anisotropic diffusion for each single object over the image. Use 5 steps, lambda in 5, and gradient threshold in 0.012.
2. Extract the boundary using graph-cut and active contours using three points of the object of training data.
3. Determinate the center of coordinate using the previous result in step 2 in the centroid of the object.

4. Calculate the spherical harmonic descriptor for the whole image using the center of coordinate defined in previous step and the process described in Section 3.1.3. Using M=3 to extract the first 16 frequencies of spherical harmonic
5. Save the description of each point of the boundary, information extracted from the boundary of step 2 and information of descriptor of step 4. This final result is our descriptor.
6. Compare one descriptor to the others of our database to find the best matching use Euclidean distance.

In order to compare two different descriptors we have two different matrixes. Because each object has different number of boundary points, while one image could have $b$ points, another could have $a$ points. So each descriptor has rows as many boundary points the image has and columns as many bands the image has. To discriminate which is closest and which is not to find the best match we use knnsearch function of Matlab 2010 with Euclidean distance as metric distance. With this function we compare each row of the object searched with each row of each object in our image or database (depend the type of the experiment). When find the smallest value this going to row corresponding to object searched. So, finally we arrived to a vector results with length as many boundary points have our object searched. The mean of this vector is the number associated to the comparison between the object searched and the object evaluated. The smallest of this value defined which the best match is. Figure 4-1 illustrates the process explained.

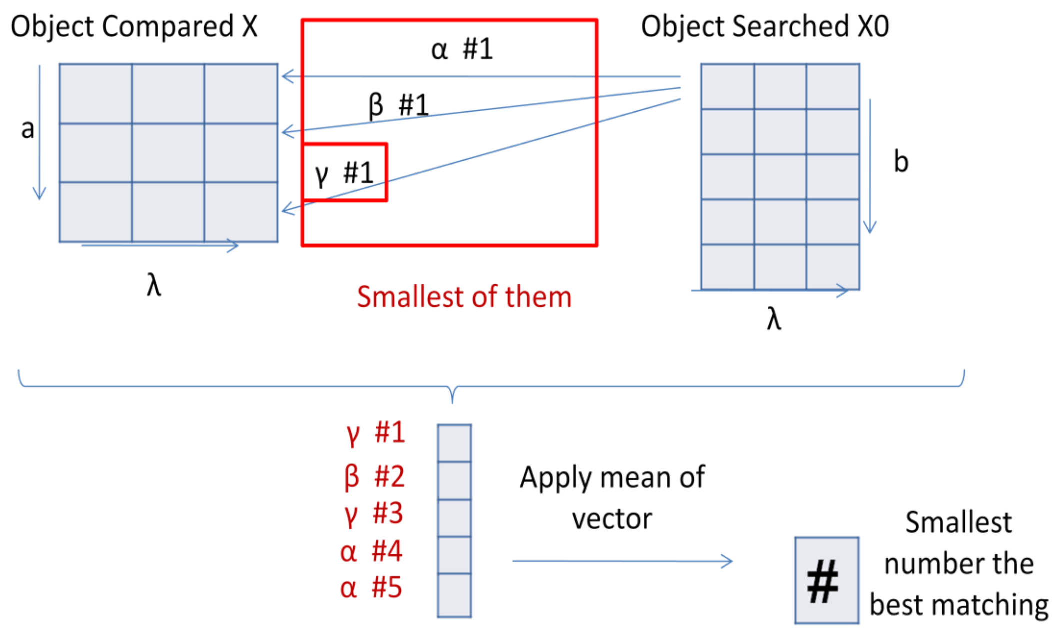



*Figure 4-1: Euclidean distance to comprared two descriptors*

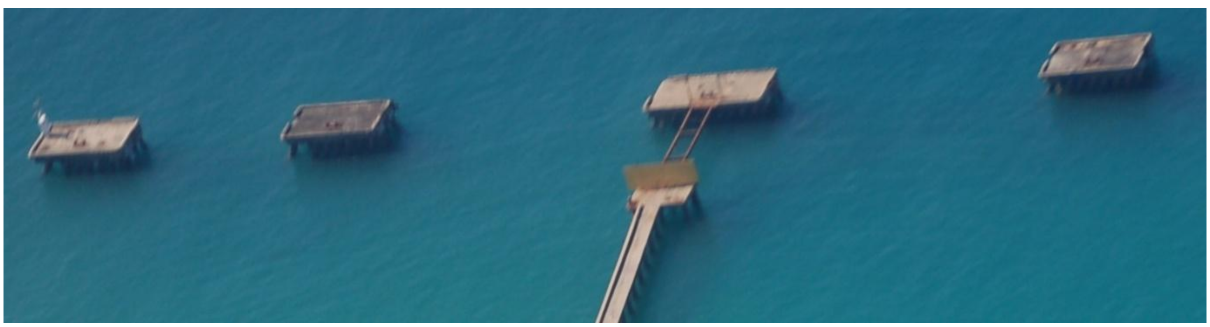
In case of object retrieval result, we order the number obtained with the comparison of object searched and each element in our image or in our database (depend of the type of experiment).

## 4.2 RGB Multispectral Imagery

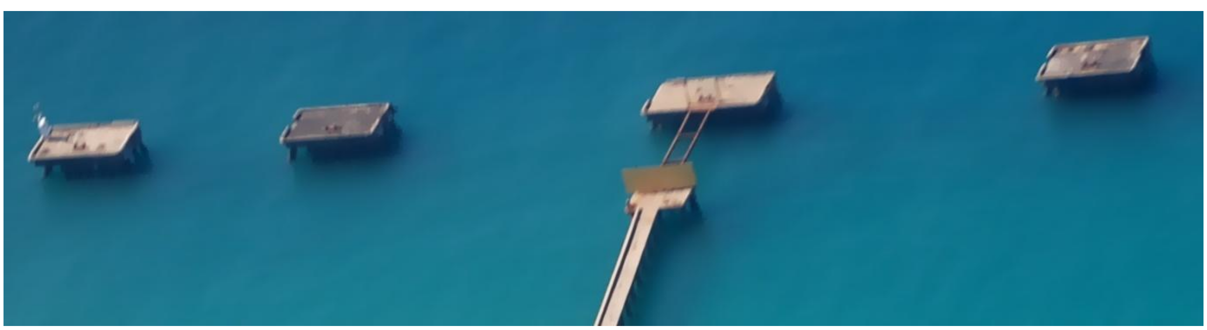
We used different aerial images; all of them were taken by aircraft over Guanica - Puerto Rico. In the experiments show below, we used a Nikon model D50, with a local length from 95mm to 200mm, and f/# from 5 to 6.3.

The experiments presented in this section belong to Experiment type 1 described in the previous section because we consider many object in a single image and try to find which element is closest to the object searched.

Figure 4-2 shows the aerial image of different identical docks. While (a) are the original RGB image, (b) is the result after applying anisotropic diffusion using 5 steps, lambda in 5, and gradient threshold in 0.012.



(a)



(b)

*Figure 4-2: (a) Original image of docks aerial image, (b) Anisotropic diffusion result*

The results of anisotropic diffusion will be the entry for the next stage: boundary extraction. Boundary extraction also called segmentation process is an important key in our algorithm because with this particular step we isolate the boundary of the object; this boundary was the shape that we are going to compare to find which match with the object that we are looking for.

Our purpose is to determine how an algorithm could extract the most similar shape with reference to an object shape even if they are located in different position, or different angle.

For example in Figure 4-2 about docks, we have four identical docks that have the same shape, but due to position of the camera each of them was captured in different angle and position around the image. With our algorithm we want to prove that if we have information about just one dock, we should find the closest similar object to the learnt dock.

Figure 4-3 shows the objects found after boundaries extraction process using bwboundaries explained in previous section. As we can see we find 10 different objects, but just 3 of them have the boundary corresponding to a dock. Hence the segmentation process is important in extracting the boundaries.

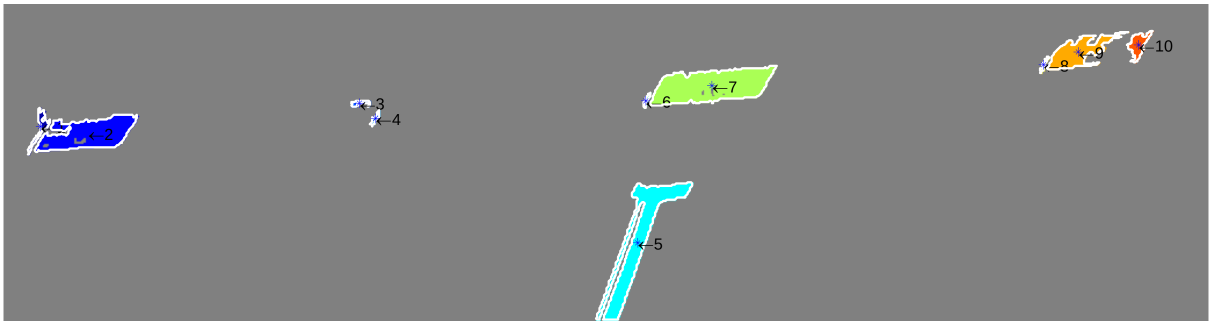
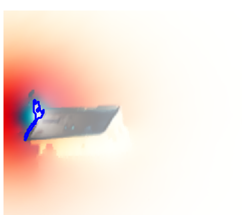
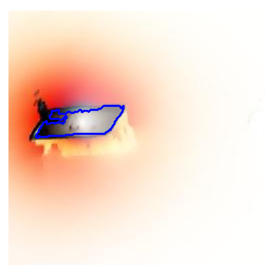



*Figure 4-3: 10 Objects found in the whole image*

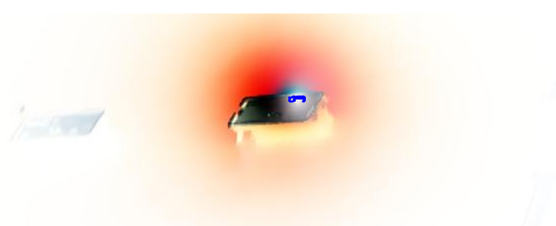
The next sequence of image show the spherical harmonic results for every object detected. Putting the origin of coordinates in each object centroid we calculate the spherical harmonic explained in Section 3.1.3 and the visualization of the results is present in Figure 4-4.



(a)

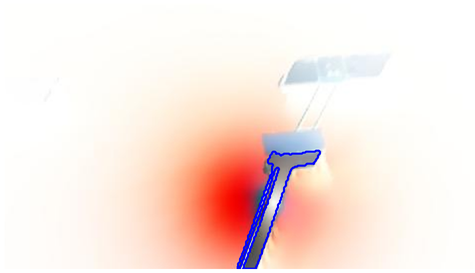


(b)

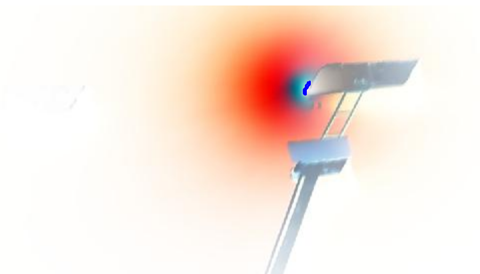


(c)

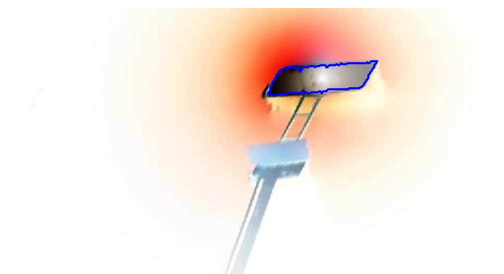
(d)



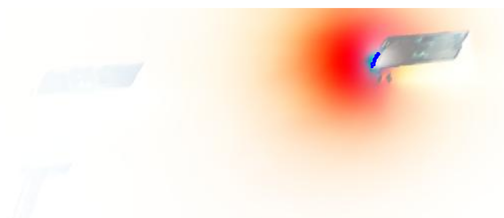
(e)



(f)



(g)



(h)

(i)

(j)

*Figure 4-4: Spherical harmonics for each object detected*

After the extraction of description over the original image, we consider the position of the boundary points for each object and extract the value of the descriptor. This information is saved to identify the object and compare to the others.

We are looking for a specific object located in the image and we get the closest shape to our object searched. In Figure 4-5 we are looking for the closest shape to the red one, and the algorithm finds the green one.

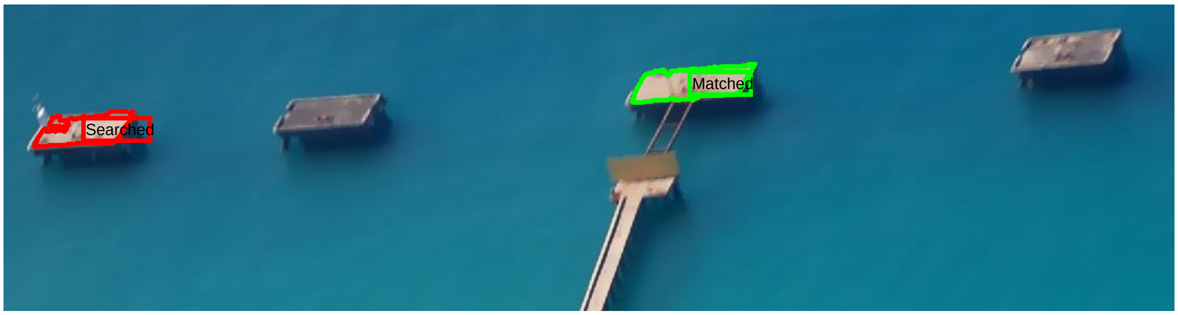



*Figure 4-5: Red one object searched. Green one object matched*

The Figure 4-6 shows an image of different identical houses. This aerial image helps us to prove if we can recognize object such houses. Every house is located in different positions, but all of them are identical. In this case and the subsequence experiment we are going to avoid presenting the spherical harmonic descriptors because visually they do not provide more information.

(a)

(b)

*Figure 4-6: (a) Original image of houses aerial image, (b) Anisotropic diffusion result*

Figure 4-7 shows the different object detected in the image, total 11 objects, but just eight objects are houses. Our purpose is using our algorithm determine what is the closest houses. Human accuracy could identify that object 6 and object 10 is the best match. The others, is also good matching but the perfect shape matching visually is 6 and 10 object.

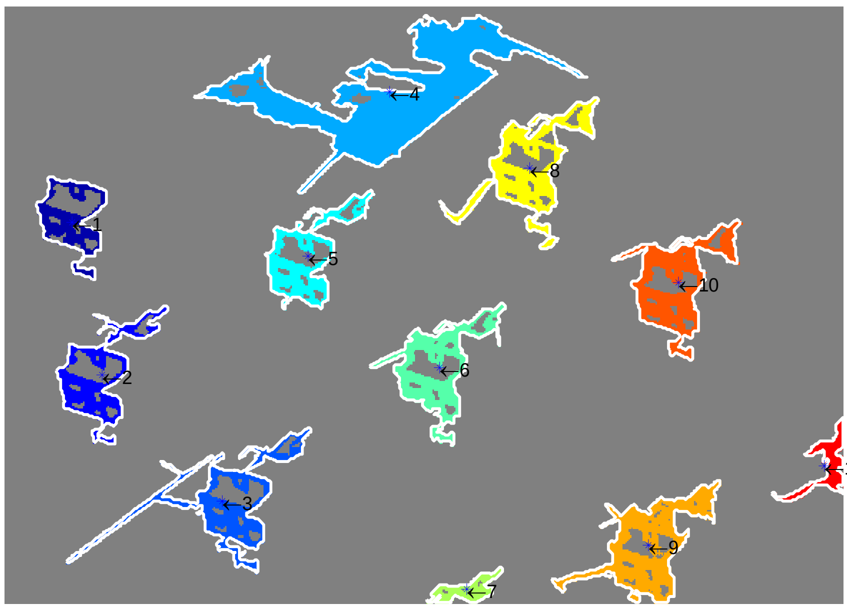


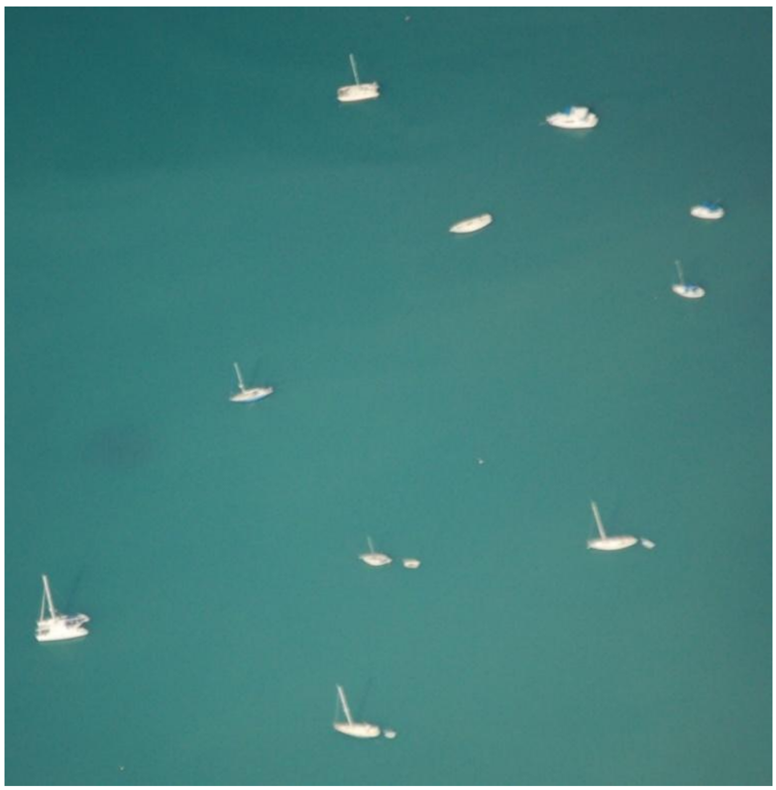

*Figure 4-7: Boundary objects detected*


*Figure 4-8: Red one object searched and green one object matched*

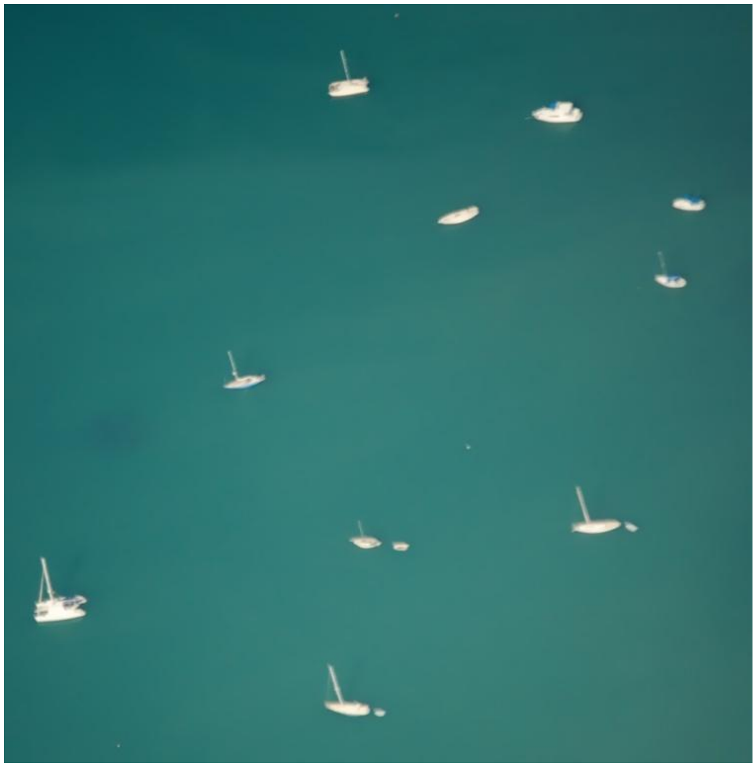
But we want to go forward, and analyzing the results of best matching, we can extract the best object matched. Ergo, the best 6 closest matching to the object searched. The perfect result should throw only the house's boundary, and we can see the result in Figure 4-9.


*Figure 4-9: Best first six results*

Finally in Figure 4-10 we show different ships. In total we detect eleven ships, there are different ships, and it is not the same like in the experiments before. In this case we have different similar objects, not identical. Each of these ships has particular boundaries, this boundary are again important in order to determinate which is closest to the searched element.



(a)



(b)

*Figure 4-10: (a) Original image of ships aerial image, (b) Anisotropic diffusion result*

Figure 4-11 shows the eleven elements. But the object [1, 2, 3, 9] are the same boundaries, because these ships have a mast. This particular distinction helps us to discriminate in better way one element from the others. If we are keeping analyzing the image we can see that the best approach to element 3 is 9. Our algorithm must throw the similar result that our visual approach. Figure 4-12 shows the result.

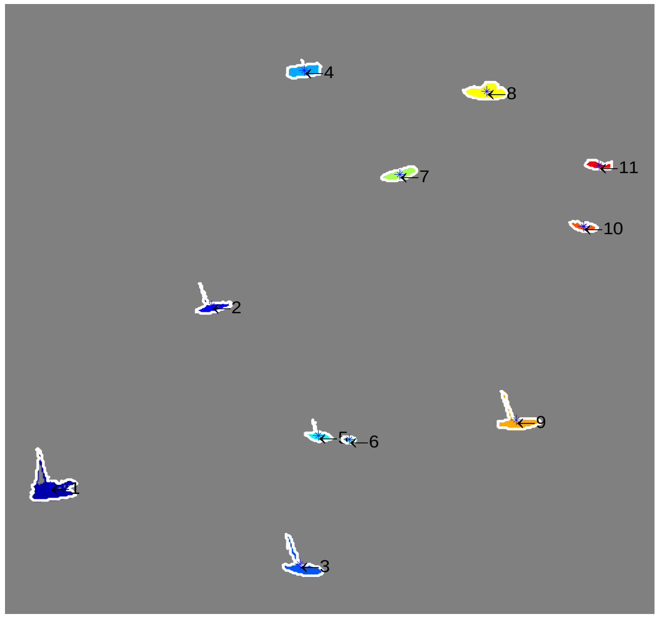



*Figure 4-11: Ships detected*


*Figure 4-12: Red one ship searched and green one ship matched*

In this case of ship searching, we do not have the better previous information about what are the exactly identical ships, so we just extract the first six elements in order of our accuracy to spherical harmonic descriptor. In Figure 4-13 show the result of the first six elements closest to the object searched.

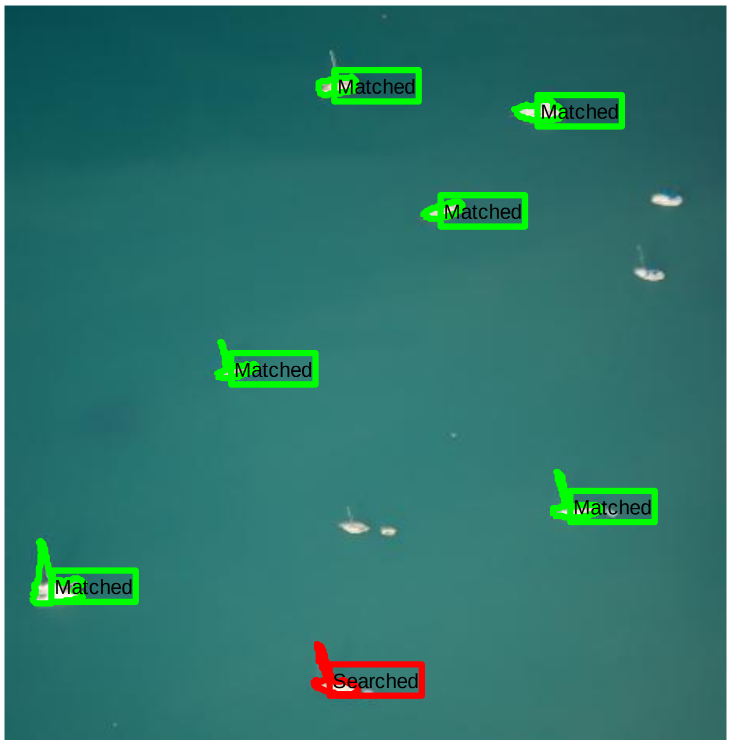



*Figure 4-13: Best first six results*

But we can improve this searching adding a threshold area. With a decision rule with limit superior and limit inferior associated with the object searched area. The area thresholding is a basic step in where we can determine if the area of the object searched is closest to the object matching; with a percentage determine by threshold we reduce the results. Figure 4-14 shows the result.

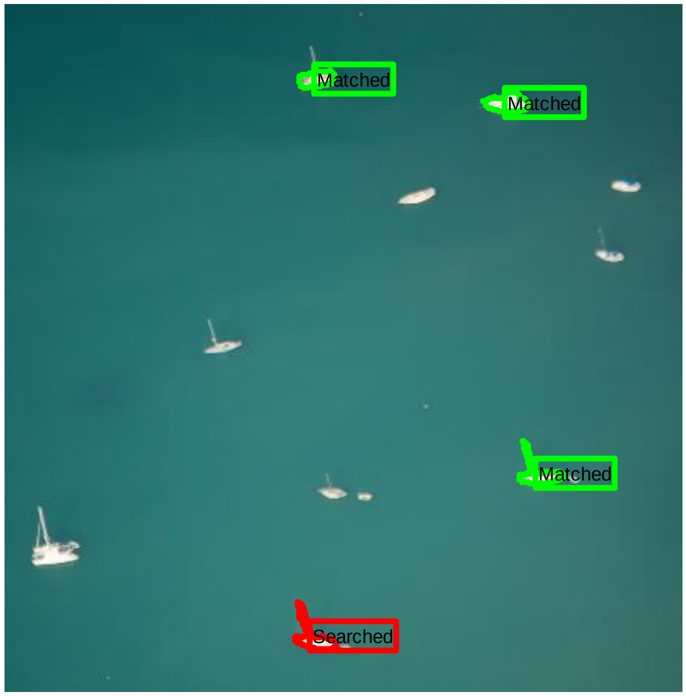



*Figure 4-14: Bests Result using area threshold*

## 4.3 Hyperspectral Imagery

This section presents the experiments with hyperspectral images. For this purpose we experiment with images captured by SOC-700 hyperspectral camera and HYDICE sensor image from Washington DC Mall.

These two experiments have different approaches because with SOC-700 camera we collect many objects and separately extract the description developed explained in section 4.1 experiment type 2 – one object per image. With HYDICE however we apply the approach of experiment type1- many objects per image.

### 4.3.1 SOC – 700 Hyperspectral camera experiments

SOC-700 Hyperspectral camera has a spectral resolution of 4nm, with 120 bands and spectral range from 400 to 1000nm. With this camera we collect more that 100 hundred different elements in different positions and different materials. Our objects collection will be called SOC – 700 hyperspectral database. Our purpose is proof how efficient works out our algorithm to discriminate object with the same material, and how recognize object even when we have same shapes but in different materials or different position or same material but different color and any kind of these combinations.

The next experiment is classified as Experiment type 2 describes in section 4.1, because we have just one object per image, and a database of object instead of many object in a single images.

Currently SOC – 700 hyperspectral database contains 108 objects. Among these all elements we searched some representative objects. In order to understand the different objects in our database we are going to present them in set joined by its type: cars, caps and geometrics objects. Figure 4-15 to Figure 4-17 show these three different groups. Inside of these general sets we have different subset. For example in Figure 4-15 we have 5 subsets: the big cars, the silver cars, the orange cars, the black cars and the blue cars.

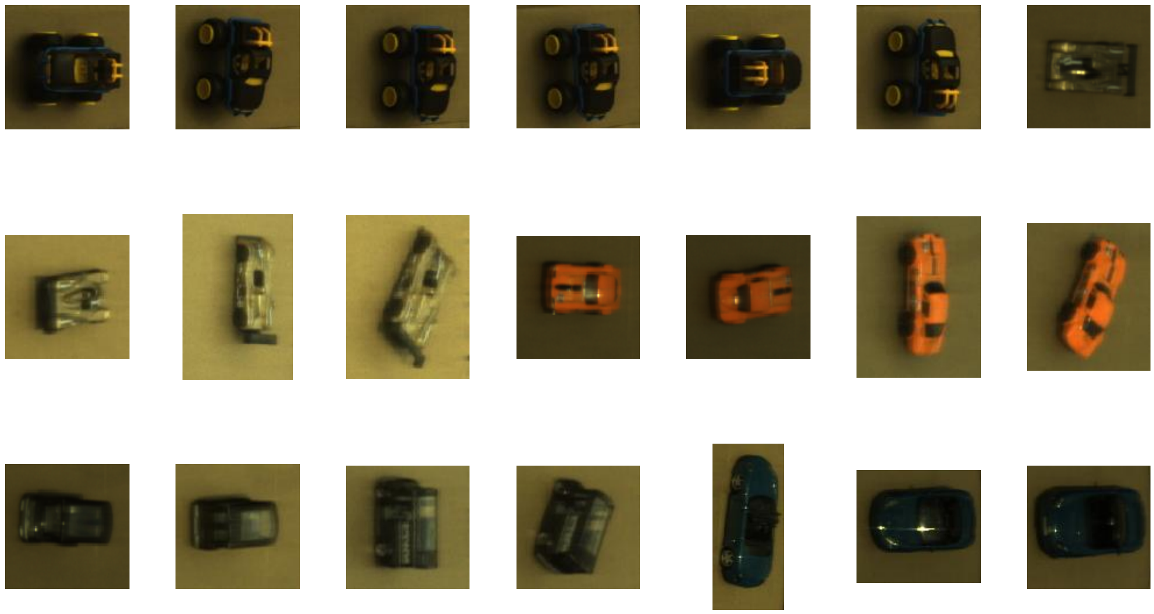


*Figure 4-15: SOC -700 Cars database*

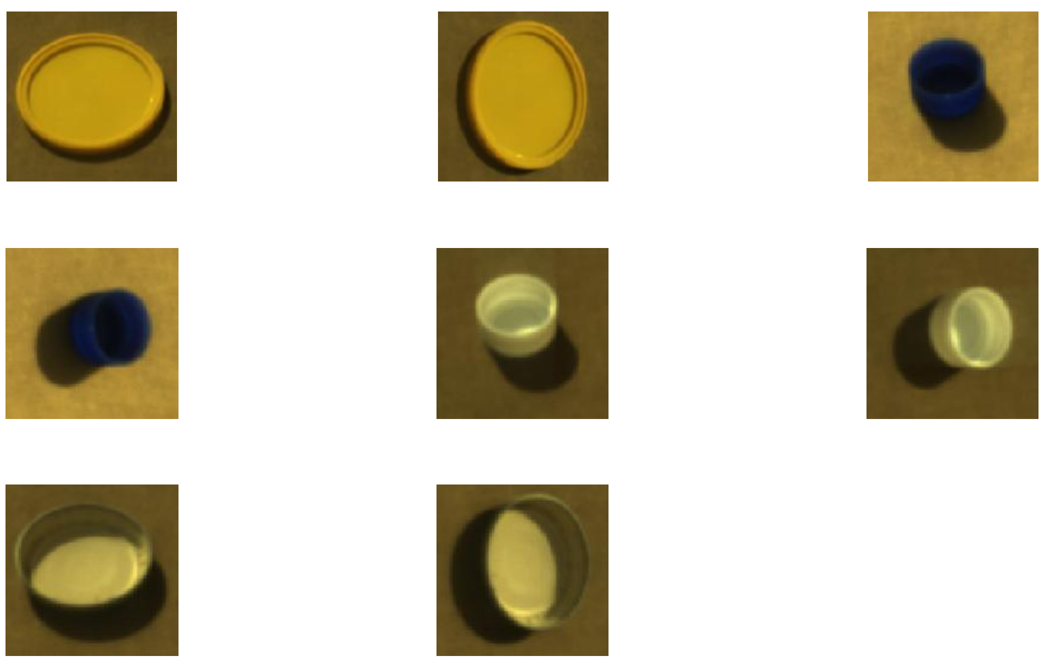


*Figure 4-16: SOC -700 Caps database*

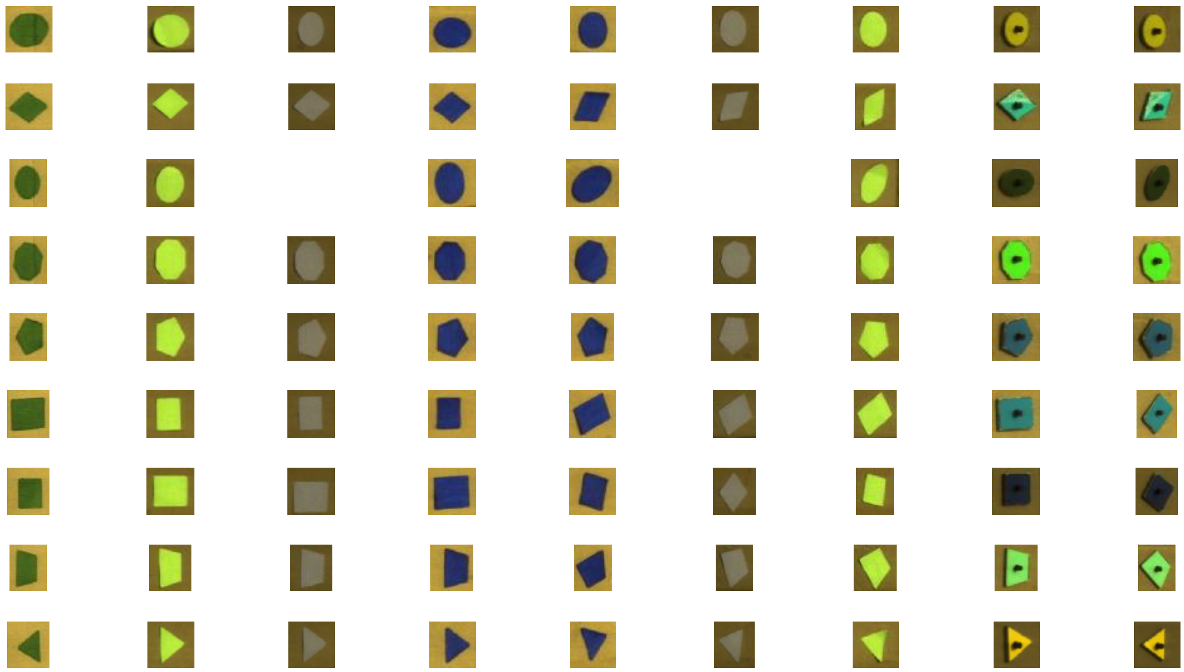


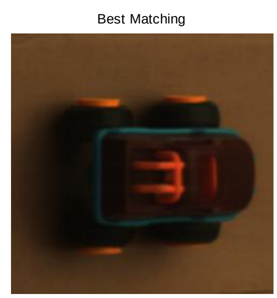
*Figure 4-17: SOC -700 Geometric objects database*

We aim to test how well our spherical harmonic descriptor using just the boundary of the object finds the same object in different position. In order to satisfy this presumption, we ran series of experiments in which we searched each representative element and matched with the different objects in our database and analyzed how well the computed ranks correlate with a human's recognition.

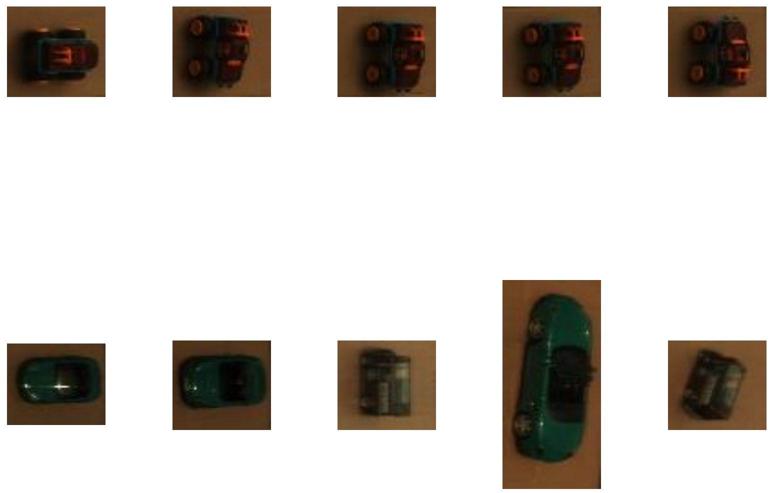
Figure 4-18 to Figure 4-20 show representative experiments to visualize the accuracy of the algorithm proposed. Adding to the spherical harmonics we added a final step in order to reduce the searching results and it was the area involved with the boundary defined in the previous step. With a threshold of this area we reduce the results to the most important matching.

Figure 4-18 shows the result searching toy car with different color, in our database this object appear five times in different positions, and perfect accuracy would be 5 of 5. The best match showed is the same car but in different position, it means a perfect accuracy. In the object retrieval results Figure 4-18 (c) shows all of five cars. Visually the results are perfect because we obtained the same object in both result objects (Figure 4-18 (c) and (d)). While in Figure 4-19 the result are a little different, in these cases the total subset for this object in our database are 2. In object matching our approach through perfect object recognition, while in object retrieval it is found the two cars in the database that are in different positions and even with different illuminations. But the result with area threshold is not good because it is missed one of the cars.

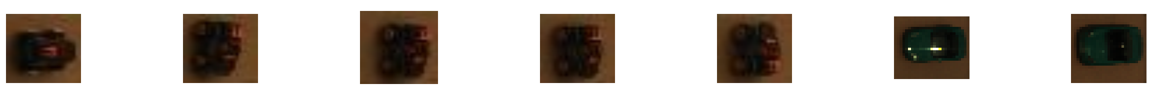

(a)




(b)

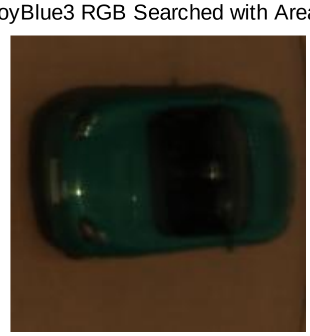


(c)



(d)

*Figure 4-18: Car Searching. (a) Object searched. (b) Best match – object recognition. (c) Ten first results – Object retrieval (d) Results with area threshold*



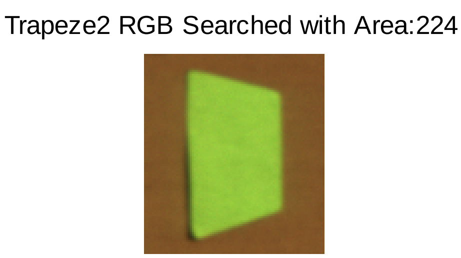

(a)

(b)

(c)

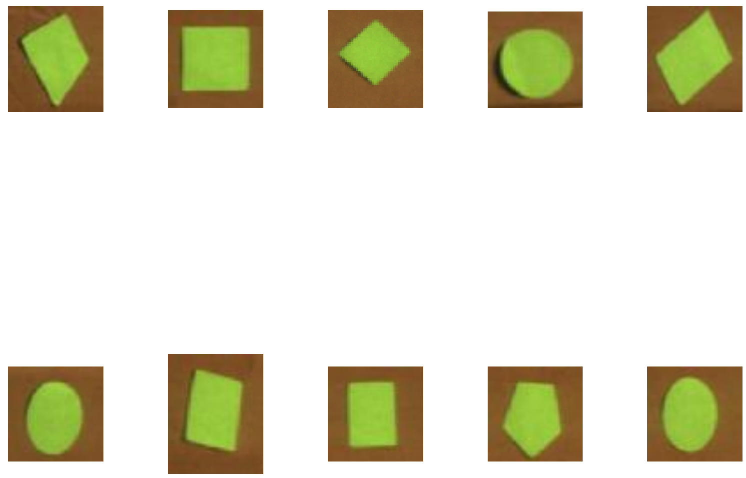
(d)

*Figure 4-19: Blue car Searching. (a) Object searched. (b) Best match – object recognition. (c) Ten first results – Object retrieval (d) Results with area threshold*




(a)

(b)



(c)

(d)

*Figure 4-20: Geometric object Searching. (a) Object searched. (b) Best match – object recognition. (c) Ten first results – Object retrieval (d) Results with area threshold*

In Figure 4-20 a little difference in the result with the previous experiments is presented. While best match is the same shape and material, that means the same object but in different position, the object retrieval identify the object and consider with major weight the spectral information that is why the results through all of object with the same material.

So, with this final experiment we can observe that the spatial and spectral information are the most important information to find the best match, that is why the software eliminates the other identical geometric figure but in different material, even if the figure is in the same position of the element searched. But once the algorithm finds the best matching the next results are similar geometric object but identical material, that means that spectral behavior is prevailing to the results after the software did not find the similar shape and identical material.

### 4.3.2 HYDICE hyperspectral sensor experiment

The HYDICE image is an urban scenario with 301 $\times$301 pixels and 191 bands collected over the Washington DC Mall. The bands were collected in the 0.4- to 2.4-μm region of the visible and infrared spectra.

This experiment is categorized in Experiment type 1 – many object per image described in section 4.1. We want to isolate first the different man-made objects; due to spatial resolution our segmentation is not our best attempt. Just 10 elements can be isolated, Figure 4-21 shows the RGB composite image and its respective boundaries extraction.

The spatial resolution for this image is 4m that means that small object such as cars represent just one or two pixels, with this kind of spatial resolution we cannot extract boundary for small objects and focus our experiment in buildings. After applied anisotropic diffusion and convert to grayscale to extract boundaries of different objects we observe that just big elements of the images are segmented Figure 4-21 (b).

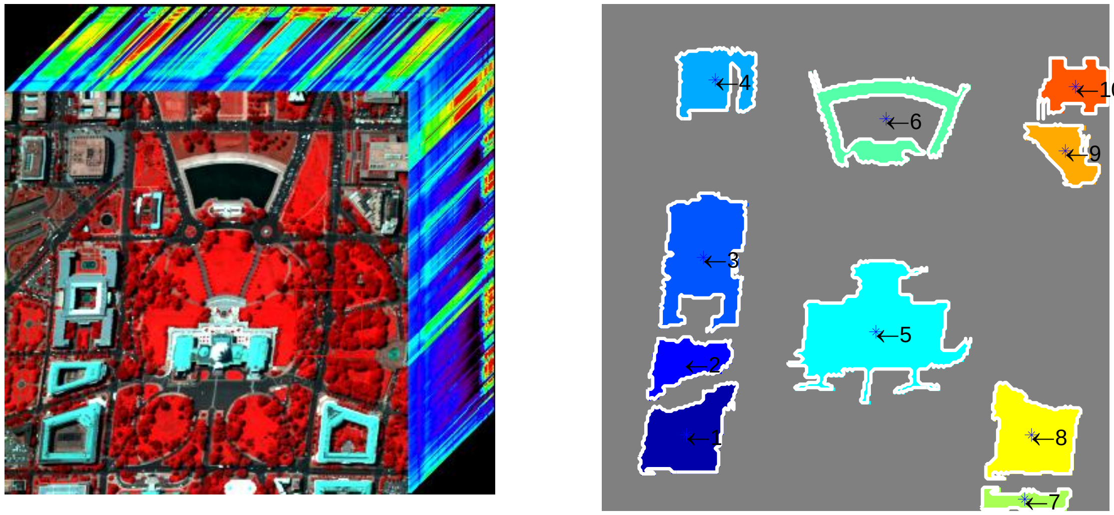



*Figure 4-21: Washington Dc Mall from Hydice. (a) RGB Composite 60/27/17. (b) the boundaries extraction total object found: 10*

In Figure 4-21 (a) we appreciate the just two elements in the Washington Dc Mall are identical, we refers to objects labeled with 1 and 8. These two elements are identical visually; because we are talking about human construction in a Mall it is not surprise that the architecture of the mall involved similar elements in order to maintain the harmony.

If we search element 8, the best result have to be element 1. In Figure 4-22 we can visualize that our algorithm with a threshold of area throw the best result possible.

This experiment shows that the spatial resolution is a big limitation in order to extract boundary. Since our algorithm is a fusion of boundary and spectral behavior around the boundary, if we could not find the boundary the next steps are poorly calculated.

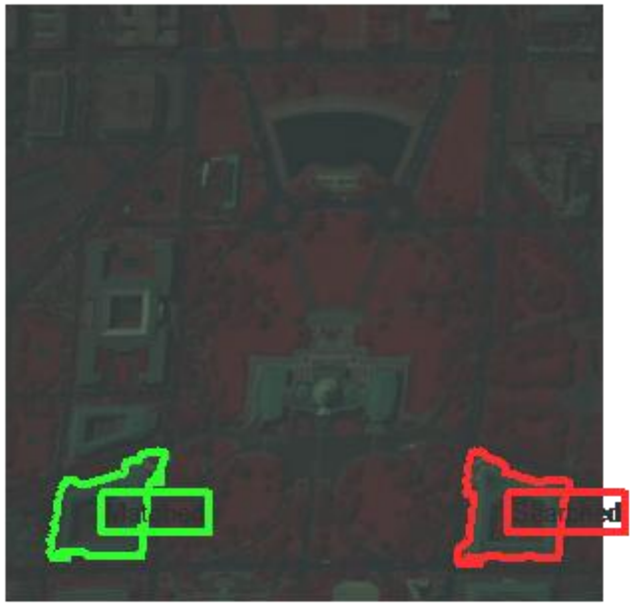


*Figure 4-22: Results of element searching*

# CHAPTER 5

# 5 Conclusion and Future Work

## 5.1 Conclusions

In this research an algorithm using a powerful shape descriptor to recognize man-made objects in RGB and hyperspectral imagery under translation and rotation transformations has been developed. This algorithm use spherical harmonic descriptor applied to RGB and Hyperspectral images.

Different researchers consider the spherical harmonic descriptor as an invariant shape descriptor to identify object under rotation and translation transformation, but no one consider an extension applied to hyperspectral images, this present thesis applied this powerful shape invariant descriptor to hyperspectral object recognition with successful results. Considering the spectral behavior of the objects around the bands gives us better recognition accuracy.

In order to develop the algorithm we consider steps for segmentation using methods such as active contour with graph cut and boundaries extraction. For good results in segmentations methods, we applied a pre processing method using anisotropic diffusion to smooth the images.

The performance of the algorithm was evaluated using synthetic data, it is synthetic because we know exactly which object was sensed. The results show that the algorithm is invariant to translation and rotation transformations and recognizes with a good accuracy man-made objects. However due to nature of hyperspectral images there are limitations over the images, the illuminations generate problem to extract the precise boundary, the shadows are ignored as well as the obstruction of the background.

There is a mixture in the border of an object in hyperspectral images because they have more than one material. This a topic of study in these days, because the spatial resolution is poorly but we can consider that defined the sensor for each recognition process the results have the same mixture thus the border extraction have the same combination of material signatures given a good accuracy in the recognition process. Despite this observation, it is still a problem to segment the object when the images are taken with low spatial resolution. Therefore experiments show that better spatial resolution the hyperspectral image has better segmentation process.

The novel tool presented in this research is a fusion of two datasets of information. From one side it is considered the spectral behavior around the bands and on other side is considered the shape behavior. Each sensor has set the spectral bands in a particular range. Since it is compared over images from the same sensor experiments have the same particular range for each image.

The spherical harmonics are applied in tridimensional image because the nature of the function is over tridimensional space. However, in this present research is developed an approach of spherical harmonic over hyperspectral information using the two dimensional nature of the image spatially talking and the third dimension of the spectrum. This consideration is not according with the theory of third spatial dimension but our approach and experiments through that the recognition accuracy and invariance transformations have been achieved.

## 5.2 Future Work

Perform some experiments with different spectral resolution, in order to find the benefits of fusing spherical harmonic descriptor with pixel spectral behavior. Different sensors means different range of spectrum, in each spectrum the data taken is different; some of them do not take in consideration the borders, this affect directly the shape behavior extraction of the novel tool proposed in this research. Analyze different sensor let us know how this omission affect directly our algorithm.

Implement other object recognition methods for RGB and hyperspectral images to compare results and evaluate the performance. Wavelets are a good method for description extraction and could be applied over hyperspectral image without have the problem of the third dimension. Despite this good quality wavelets are still not invariant to rotation and scaling and this kind of limitations generate a less powerful tool. However comparing these two approaches it could be defined which gives more to recognition accuracy.

## 5.3 Contributions

### 5.3.1 Publications

Fanny Nina-Paravecino and Vydia Manian, “Spherical harmonics as a shape descriptor for hyperspectral image classification In Proceedings of SPIE: Algorithms and Technologies for Multispectral, Hyperspectral, and Ultraspectral Imagery XVI, Vol. 7695, April 2010.

### 5.3.2 Poster Session

CenSSIS RICC at Northeastern University, Boston, MA. October 18th – 19th 2010.

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