#### SATELLITE IMAGE PROCESSING USING LOW LEVEL SYMBOLIC STRUCTURES

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## 1. DIGITAL PROCESSING OF SATELLITE IMAGES

A trend that has been observed is the improvement in both the spatial and spectral resolution in satellite images. This has two consequences regarding their digital processing by computers. First is the huge volume of data that will have to be processed and, second, is that, due to the "richness" of the image, the processing will resemble more and more that of a human interpreter. Also the number of different satellites presently available or programmed for the next years adds to the amount of data that has to be processed. In other words, to be able to effectively extract timely information, one has to rely on automated processing; moreover, this processing has to be much more sophisticated.

Traditionally, the processing of satellite images has been directed to making the images more suitable to human analysis. Examples of typical processing are the restoration and correction of images (both radiometric and qeometric), enhancement of features of interest and spectral band combination. What is common to all these examples is that the input to the processing is an image and the output produced is also an image. Non-pictorial information extraction has been mostly restricted to pixel classification, like in crop area estimation. This type of processing uses only a fraction of the information that is normally available, explaining why the results obtained are often so unsatisfactory.

The idea behind the work reported in this paper is to apply concepts and theories proposed to explain some aspects of visual perception (Marr 1976, 1982) to the processing of satellite imagery. Our ultimate goal is to build satellite image processing systems capable of degree of some "understanding". By understanding we mean the ability to identify the objects in the scene relevant to the application and describe their relationship in terms of the application vocabulary.

Computer vision systems are usually organized hierarchically in modules that process the information at various levels of abstraction (Brady, 1982). The modules that constitute the low level vision deal directly with the image or with transformed versions of it. These modules encompass most of the traditional image processing. Here the input is the original

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scene and the output is a semi-pictoric representation of the image, called "intrinsic" or "parametric" image. The next level in the hierarchy, intermediate-level vision, bridges the gap between the parametric image and non-pictorial symbolic representations. A typical task in this category is image segmentation, where the output is a list of objects and their attributes. The last step, high-level vision, manipulates abstract symbolic representations and outputs the final scene description.

In this work we are concerned with the first step, low level processing. We define and extract a low-level symbolic representation (primal sketch, Marr 1976) that can serve as a basis for all subsequent processing. In particular, we show two examples of its application: the extration of linear features for geological mapping and the segmentation of a satellite image (TM sensor).

# 2. LOW LEVEL IMAGE REPRESENTATION

The simplest representation of the image is the array of pixel values. For vision purposes, this representation is considered to be too crude and noisy to be directly useful. For this reason, a better representation was sought. In this work we adopted the "raw primal sketch" which was proposed by Marr (1976, 1982) as the basic representation. The raw primal sketch can be considered the starting point upon which grouping and selection processes operate, producing the "primal sketch". In Marr's theory of human vision, these processes are independent of the the other modules (intermediate and higher). In our work we made it dependent of the application because it is not our intend to build a general purpose processing system (as is human vision). Figure I shows a block diagram of the main processing steps. The block "secondary processing" represents the grouping and selection process that are application dependent.

|       |    |          |    |        |    |   | -    |        |
|-------|----|----------|----|--------|----|---|------|--------|
| IMAGE | ĺ  | PRIMARY  |    | RAW    |    | SECONDARY   |      | FULL   |
| INPUT | )  | PROCESS  | )  | PRIMAL | )  | PROCESSING  | )    | PRIMAL |
|       |    | ING (PP) |    | SKETCH |    |   | 1    | SKETCH |
|       | 11 |          | 11 |        | 11 | ntrita radio nalio strate azur ajala escu cilitai inter nimu un | . 11 |        |

Figure 1. Low level processing steps.

Although the raw primal sketch is a representation that is obtained early in the processing, it already has a symbolic nature. It contains explicit information regarding intensity variations of the image that correspond to actual physical events in the scene. The primitives of the raw primal sketch represent various kinds of intensity variation. The main steps to obtain this representation are:

"smoothing" of the intensity image;

2. detection of intensity variations.

The first step aims to minimize noisy variations and define the resolution or scale in which the variations are to be detected. The detection of variation can be performed by first or second order derivatives. If first order derivative is used, one should look for "peaks" in the derivative; if second order derivative is used, intensity variations correspond to "zero crossings" of the derivative.

Psicophysical and neurophysiological considerations pointed towards using the bi-dimensional Gaussian filter as smoothing operator and the Laplacian filter as the derivative operator. Marr and Hildreth (1980) showed that, for linear variations, the zero crossings of the Laplacian operator of the Gaussian filtered image are representative of the local intensitv variations. Also, under certain conditions, the original image can be reconstructed from the zero crossings alone, indicating that there was no information loss in these conditions. The Laplacian and the Gaussian operators can be combined in a single operator that is convolved with the image. From the convolved image the the zero crossing points are detected, resulting in the "zero crossing image". All the primitive objects that compose the raw primal sketch are extracted from this image.

The basic symbolic primitive of the raw sketch is the "zero crossing segment". These are obtained by grouping zero crossing points in short straight segments. These primitives represent the intensity variations at a given scale. The segments are characterized by the attributes: position, length, contrast and orientation, as shown in the following data structure.

| (SEGMENT | (POSITION  | Х  | Υ)                   |
|----------|------------|----|----------------------|
|          | (LENGTH    |    | Τ)                   |
|          | (CONTRAST  |    | с ( С ) <sup>с</sup> |
|          | (ORIENTATI | ΟN | D))                  |

The position can be calculated as the center of the zero crossing points that originate the segment. The size is simply the number of zero crossing points. The contrast can be defined as the average of the zero crossing contrast and the orientation can be obtained from the zero crossing orientation is given by the gradient of the convolved image at the zero crossing point).

Another object of the raw primal sketch is the "bar". A bar consists of two segments, approximately parallel, that are separated by a small distance (Hildreth, 1980). The descriptor for the bar is the following:

| (BAR                 | (POSITION X    | Υ)      |     |     |          |
|----------------------|----------------|---------|-----|-----|----------|
|                      | (LENGTH        | T)      |     |     |          |
|                      | (CONTRAST      | C )     |     |     |          |
|                      | (ORIENTATION   | D)      |     |     |          |
|                      | (WIDTH         | W))     |     |     |          |
| where the length is  | given by the   | length  | of  | the | largest  |
| segment, the width i | s the distance | between | the | two | segments |

and the other attributes are computed in a straightforward way from the two segments. Bars are important to relate variations of different scales, as the same variation can originate a segment in a scale and a pair of segments in a larger resolution.

While segments and bars are derived from a single scale (defined by the Gaussian filter used), the next primitive, the "border" is obtained combining different scales. A border originates if two primitives of the same kind and similar attributes exist in two different (but contiguous) scales. The descriptor for the border is the following:

| (BORDER | (POSITION X  | Υ)   |
|---------|--------------|------|
|         | (LENGTH      | - T) |
|         | (CONTRAST    | C) - |
|         | (ORIENTATION | D)   |
|         | (WIDTH       | W))  |

where witdth in this case refers to the width of intensity variation that, along with the contrast, give how steep is the intensity variation.

The segment, the bar and the border define our raw primal sketch that provides the basic representation upon which the following processes are based.

3. SOME EXPERIMENTAL RESULTS

### Geologic mapping

One kind of geologic mapping is the creation of maps showing faults, folds and fractures of a region of interest. This involves the detection of linear features from the image which usually is tedious and error prone. Because of this, some efforts have been directed to automating this task (Abrams et al., 1985).

Our first experiment was to use the raw primal sketch as the basic tool for linear feature extraction. For this we used band 5 of the TM LANDSAT sensor. The area analyzed is situated in the Minas Gerais state, Brazil. For the experiment two scales were used: one with Gaussian operator diameter of 6 pixels and another with diameter of 10 pixels. Figure 2.a shows the original image, Figure 2.b shows the extracted primitives and Figure 2.c depicts only primitives with 45 degree orientation.

In this example, the processing after the extraction of the raw primal sketch consisted in selecting all primitives oriented towards a given orientation.

### Image segmentation

In the second experiment, the raw primal sketch was used to segment an image through a grouping process. The object of interest was a river, in the Assis region, São Paulo state, Brazil. The Gaussian filter sizes were the same as the ones used for geologic mapping. Segments in the raw primal sketch were grouped based on continuation and proximity. The results can be seen in Figure 3.

### 4. CONCLUSIONS

In this work we propose to use a symbolic low level representation - the raw primal sketch - in satellite image processing. This departs from the traditional usage in several ways and is, we believe, a necessary step towards building satellite processing systems capable of some degree of comprehension of the images under analysis. The raw primal sketch can be further processed (selection and grouping) so that the information needed for the application is obtained. While the sketch can be the same for all applications, the extra processing is directed by the application.

Two experiments were performed: geologic mapping (extraction of linear features) and image segmentation. The results were considered very encouraging as the representation proved to be both general and adequate. The fact that after obtaining the raw primal sketch very little processing was performed shows the adequacy of the representation. Also considering the diversity of the applications the results show the generality of the representation.

#### 4. REFERENCES

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(b)

(c)

Figure 2. (a) TM, band 5 study area; (b) Raw primal sketch primitives; (c) Area with 45 degree primitives.



(b)

(c)

Figure 3. (a) Original image; (b) River segments; (c) Image selected and grouped segments.