SEMANTIC-MIND ANALYSIS AND OBJECTED-ORIENTED DATA INTEGRATION OF VISUAL INFORMATION: A PRIMER♥

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ABSTRACT
A companion paper in this book emphasizes the emergency of computer-based intelligent analysis of digital information flows, provides some prompting toward its solution, and sketches an approach to intelligent data (audio, images, video, mixed) analysis and synthesis. In the present paper, we describe how to extract semantic components from unordered data sets (Gestalt problem) in visual information data (*Analysis*). An application of our approach is illustrated by describing a raster-scanned color cartographic map interpretation system—*Analogical-to-Raster-to-Vector* (A2R2V).

KEY WORDS
Semantics, Information flow, Visual data, Semantic-mind analysis, Object-oriented data integration, Semantic analysis of cartographic data.

1. INTRODUCTION

For the sake of completeness, we reproduce here some definitions that have been introduced and discussed in the companion paper in this book [20].

Information flow (IF) is binary digital data stored and processed by the computer. This is the basic element of digital technologies. On the other hand, IF is data that derives come from the outer (to the computer) world and that have very different representations— environmental monitoring, text, music, speech, images, etc. At present, the problem in adapting computer systems to human perception and cognition is apparent (MPEG-7), but not yet carried out. In the present work, we would like to describe some applications of *Semantic-mind analysis* (SMA) and *Object-oriented data integration* (OODI) of IF by following the methodology proposed in [20]. These applications aim to show within the general context of the human-machine interaction the semantic approach to computer data analysis and synthesis.

"*Semantics—the study of the meanings of words*" [2]. Therefore, semantics is the search for cognitive, associative object identification in IF. Keywords in text, sound-shapes in audio flows, segments in image flows (data invariants), etc. are object-oriented data of IF.

"*Mind—the part of the human being that governs thought, perception, feeling, will, memory, and imagination*" [2]. In other words, meaning is the ability to understand, to feel, to perceive and to imagine, i.e., restoring a whole knowledge by some segment or part. For example, the program Guess a Melody [3] identifies the musical piece by a few musical phrases; the raster-to-vector conversion system A2R2V [4–6, 9] is oriented toward searching for names of converted set of pixels, thus, object-oriented data integration to *Geographic Information System* (GIS).

On the other hand (See above), semantics is the adequate, meaningful search for *words* in IF (e.g., Google search www.google.com as zero approximation), while meaning is the extraction of *subject domain* in IF (e.g., the adaptation of a Physics textbook or the articles of a specialized journal for secondary school).

Subsequently, *Semantic-mind analysis* (SMA) of IF is the meaningful search for object names and definition of the subject domain as a set of found names (e.g., 32 letters require five bits of information by Shannon, while the same letters require fewer bits of information by Morse. The difference is that the Morse Code takes into consideration frequency of use of letters in text and named the letters by symbols—dot, dash). *Object-oriented data integration* (OODI) is input into a particular computer-based application of the output of SMA. This input suggests special SMA-output data organization, compression, storage, processing, etc. dependent on that application. For example, vector object integration to GIS is straightforward. Moreover, it is far superior to store that object in GIS under the corresponding name only. In the following, we will use the abbreviation SMA/OODI for newly introduced concepts.

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Cartographic data (CD) (raster or vector) as IF are one of the most complex subjects for SMA/OODI because they simultaneously contain different types of information carriers: graphics; images; texts; symbols, etc. [6].

Our method is object-oriented, while the majority of state-of-the art approaches are pixel-oriented [11−15]. Pixel-oriented methods are artificial and destroy most essential image characteristics, including general composition, object shapes, image dynamics, and contextual information. All this results in increasingly complex methods and algorithms for machine recognition of data objects based on pixel-oriented approaches that do not materially improve the results. The majority of effective image formats preserves the natural image structure and thus provides object-oriented data integration. This thesis is especially true for cartographic images that being intermediate between man-made drawings and natural images provide a nearly ideal model for SMA, and OODI is quite natural here within the context of GIS. More arguments are to be found in the [1, 4, 5, 6, 9, 20] (See [7] mathematical morphology approach and fuzzy approach [18] with similar ideas to GIS-ready data processing).

In [1], we considered one of the applications of our approach to audio information flows. In particular, we detected the semantic components from '*Für Elise*' by Beethoven. We compared our object-fitting hierarchical compact decomposition with wavelets and fractal decomposition and in addition gained better-structured and nearly twice the amount of compressed signal representation. Moreover, in decomposing the signal by our method signal objects were partitioned into a natural hierarchy with no additional procedure.

The goal of the present work is to apply SMA (analysis) and OODI (synthesis) in the case of visual information flows (*Analysis*) and in particular for cartographic raster data (*A2R2V*).

2. ANALYSIS

In this section, we shall explain how visual data can be transformed into their semantic-mind representation by describing the system termed *Analysis*—first SMA/OODI application.

The majority of image processing methods such as wavelets and fractal decomposition or texture analysis usually miss the vital components—the semantic structure.

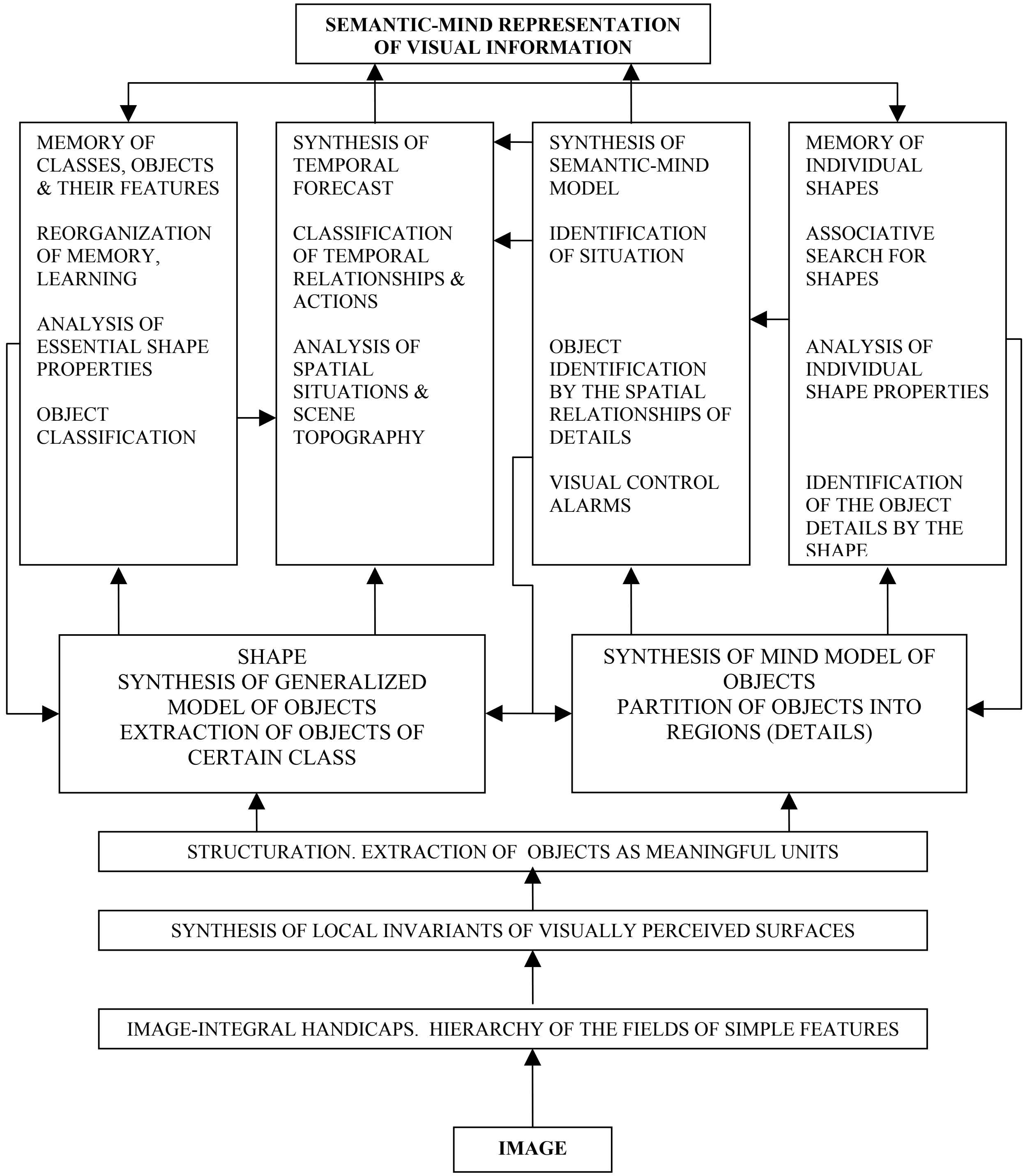
In our approach to visual information structuring, called the Analysis system, we apply adaptive dynamic data structures for object-fitting hierarchical analysis of video-data. This system is a tool to reveal interrelated networks of context independent semantics of the initial data structure.

Our approach is based on location of semantically important image segments using a rating principle and subsequent iterative synthesis of hierarchical dynamic trees to build the coherent structure of selected segments. Our considerations have led us to the idea that distribution of segments ($\boldsymbol{F_l}$) and levels ($\boldsymbol{l}$) of a tree correlates with the growth law $\boldsymbol{F_l \approx l^{-0.618}}$ similar to the empirical Zipf's laws [10].

Adaptive dynamic data structure is the result of the structuring process and contains image segments, which are essentially important for subsequent image processing and understanding.

The most evident application of image semantic decomposition is preliminary structuration of video-data for subsequent object identification and target-oriented compression of images.

To transform visual information into its semantic-mind representation, we used the previously method of associative dynamically adaptive data tree-structures. Flow chart 1 shows the computer-oriented scheme of transformation of visual data into the semantic-mind model [1, 20].



Flow chart 1: Transformation of visual information into semantic-mind representation.

2.1 MAIN COMPONENTS OF ANALYSIS

The majority of segment location methods require initial partition of the image into a set of segments. The main problem with this non-trivial task of image analysis is lack of general methods for reasonable segment selection. We used the semantic-mind approach to overcome this difficulty [1, 20].

Analysis is oriented toward revealing the independent semantic contents in source data. The task is to build context-independent hierarchical networks of flat and spatial structures that set off this system from others.

A next step is generalization of Analysis into image synthesis. The combination of image analysis and synthesis would allow application of new methods for image processing and development of semantic-oriented compression systems.

Application of Analysis focuses on the problem of effective and optimal data storage. We solve this problem by selection and storing only semantically important data.

We have been developing the iterative method for object approximation by means of multilevel image segmentation [1, 16]. The hierarchy of source image segments tends to form the original adaptive dynamic data structure, which can be used to preserve semantic relationships of independent image parts. Elements of this data structure should be meaningful and recognizable for the human operator or automatic programs processing the image.

To solve the problem, the following algorithm has been designed:

- Source image is presented as *RGB* color-divided matrix. Pixels of the same color are segments of the first-level image partition (seeds).
- At subsequent iterations, the program merges segments whose color components contain little divergence, i.e., the differences among them fit into the selected range. In alternative cases, independent structure can be built for each color or gray-level component of the converted image. Special recursive procedure controls connections between segments and homogenizes processing throughout the entire picture.
- The process results in an interrelated semantic network of image segments that is the pyramidal adaptive structure for dynamic image representation.
- Source image I^* is transformed into special computer representation I—the set of $a \times b$ pixels.
- For effective image processing, it is necessary to change the image structure once again: image I is represented as a hierarchy of segments. m^{th} level of this hierarchy $L_m = \{F_p \; p \in D_m\}$ contains segments defined by the set of segment indexes D_m, where $I = \cup_{p \in D_m} F_p$. Links between segments correspond to edges of the indexed tree with special organization in which each segment is a tree node.
- An element of m^{th} level is denoted F_p^m. Segments of the first level are pixels of image I: $L_1 = \{F_p^1 \mid 1 \le p \le a * b\}$.
- Segment construction procedure validates the following equations for segment number in different levels:

$$\# L_i > \# L_{i+1};\ \# L_{255} = 1;$$
$$\forall p \in D_m\ \exists q \in D_{m+1}: F_p^m \subset F_q^{m+1}.$$

Object location in terms of this structure is equivalent to location of segment networks with suitable node attributes (color, gray-level, spatial, or more complex segment characteristics). The essential problem arises when no coherent segment network corresponding to the required segment is found. This predicament is the main obstacle to full automation of image analysis in this approach.

To overcome this difficulty, Analysis allows the user compulsory manual restructuration of semantic structure. This restructuration can be considered a manner to apply user-oriented pragmatics to image analysis.

The main objective of our system is assistance in the search for practical solutions in general fields of image analysis and problem-oriented restructuration of video-data. This is reached by means of location of image-semantic information and subsequent processing of meaningful image segments.

Basic components of Analysis are the following [1]:

- Algorithm of detection of equibrightness (gray-level) and equicolor segments. Homogenization throughout the entire image of segment features, using dynamic global thresholding (thresholds that are required for detection of certain segments); thus, it is adaptive to different contexts.
- Mechanism of secondary indexing of detected segments, which are organized as dynamic, irregular trees of the hierarchical relationships of these segments.
- Procedure of restructuration of image segment relationships to satisfy to operator visual control requirements and respond to alarms.

Note that possible applications of Analysis are immediate development of the following methods:

- Semantic relationship analysis with contextual image processing as problem-oriented video compression.
- Tree-structured synthesis as replication of real-object structures.
- Morphologic image classification.

Based on analysis of different computer formats, we arrived at the conclusion that most effective formats preserve natural image structure and thus the conviction to use the SMA/OODI-based approach.

In contrast, pixel-oriented methods are artificial. They destroy the majority of essential image characteristics—general composition, 2D and 3D object shapes, image dynamics, and contextual information. Pixel image representation requires line-ordered description of pixel characteristics, while image compression, restoration, analysis, and object location utilities require different data organization and formats. Such a format group includes vector image representation, fractal compression, wavelet decomposition, and a number of special image formats that store only important information; the best known instance of the group is optical character recognition (OCR) programs that transform source image into lines of text.

Due to the huge amount of information required in satellite and cartographic image processing, the thematic search for video databases, etc., effective automatic methods of image analysis to detect objects and set of image segments to carry out semantic upload emerged and have motivated this research.

2.2 IMAGE-SEMANTIC COMPONENTS

Segments were obtained as the result of the iterative procedure of successive increasing of admitted gray-level and color thresholds in segment-merging form, subsequently increasing pyramidal hierarchical structure of flat segment networks §2.1. Each segment of this structure can have the ancestor or descendant. Thus, structure obtained is called *the adaptive-dynamic data structure*.

The segment of image is a node of this spatial structure, whose attributes are primary numbers defined by averages of color/gray-level segment features and a set of pixels that represent the area and shape of the segment. This allows to organize the object-oriented identification of semantically meaningful image regions. *Image semantics* in this context corresponds to association of segments of different hierarchical levels identified with identifying conceptions from the subject domain (e.g., for cartographic data, detection of a segment identifying a coastline or highway becomes semantically meaningful. Further, this segment is renamed as coastline, highway, etc.).

As mentioned previously, Analysis involves the interactive procedure of *compulsory restructuration* of segment relationships as pragmatic tools of semantic analysis of visual data. In other words, the system's learning and self-learning with the prescribed set of associative identifiers are possible in the interactive or semi-automated regime.

2.3 CRITERIA OF OBJECT DETECTION

Of course, the problem of image semantic component detection is not trivial. However, some formal criteria for image characteristics that appear to be semantically meaningful for humans can be defined. One such criterion that we have used is the hyperbolic law of the form $1/F^a$, where $a = 0.618$, similar to Zipf's distribution [10].

Statistical distribution of image segment number on levels of segment hierarchy shows this hyperbolic regularity. Figure 1 displays the results of experiments with six test images and represents dependence of region number (n) on level number (N) in segment hierarchy

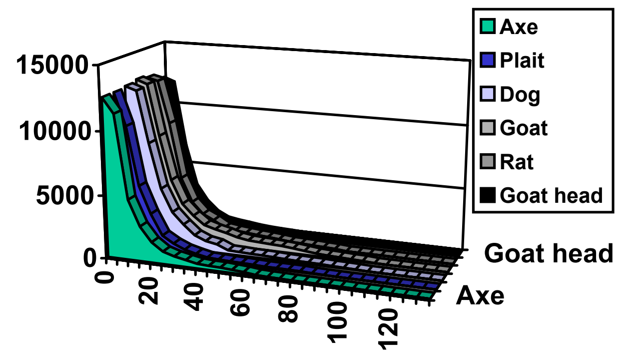


Figure 1. Rating distribution of amplitude and color regions.

The criterion of segment merging by close gray-level values was used (Figures 2a and 2b). This merging procedure is essentially different from traditional reduction of the color palette.

Similar hyperbolic regularities have been obtained not only with photos, raster images, etc. but also with the images of the realism and pseudo-realism paintings [20].

Figure 2a: Test image Axe at different semantic levels.

Figure 2b: Test image Plait at different semantic levels.

2.4 OBJECT LOCATION UTILITIES

Successive segment merging by such a criterion leads to segment structuring in a *multilevel hierarchy*. This hierarchy or multilevel image partition is an efficient method of semantic identification of the image's objects. Relationships between dynamic tree nodes indicate *neighboring semantically meaningful regions*. Because the image's regions are identified by corresponding tree nodes, *the neighbor relationship* among them can be completely defined by a table of adjacency. Modification (elimination of some edges, i.e., segment relationships) of the dynamic tree allows modifying the resulting region; thus, most exact object detection is reached. Each level of the tree of segments can be considered as alternative image interpretation in different semantics (Figures 2a and 2b; see also Figure 5, Section 4).

Adaptive dynamic tree structure regards the search for meaningful objects as fitting of *the object features* (color, location, geometry, topology, attributive information, e.g., the object's name from subject domain if known, etc. that on the whole defines *the notion of image semantic object*), to corresponding ranges and the following analysis of all admitted objects. This renders possible the use of automatic learning algorithms when the set of required objects is given and when it is necessary to define only corresponding feature ranges. The learning process can be organized as follows: User selects appropriate level of segment hierarchy and points out the set of suitable objects. These objects can be defined by merging object segments. Then, the program computes characteristics of located segments and relationships among them and establishes formal criteria for the search for similar objects. Figure 3 shows an example of associative-dynamic data structure.

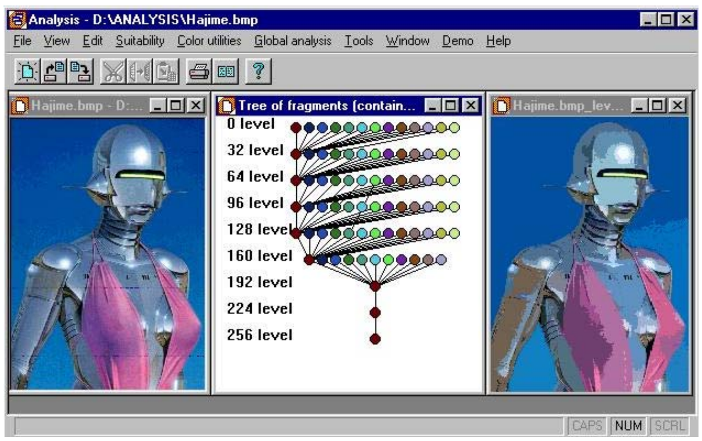


Figure 3: Example of associative-dynamic data structure.

2.5 EXAMPLE

To illustrate segment location, we use the following example: Source image is the segment of the earth surface (Figure 4a). The task is to segment land from sea.

First, we should construct the tree of segments.

Next, we select the appropriate level (64th) of tree structure, in which searched areas are approximated by segments of similar scale.

According to our task, small-scale segments that consist of one or two pixels are not essential. To visualize the different segments, we use contrast mapping of this level (Figure 4b).

From this mapping of semantically meaningful areas, we can point out any of the ground segments (it is shown in blue—the 1st node in the 64th level of the adaptive dynamic data structure).

To select all land surfaces, we need to edit the segment tree and join all land segments.

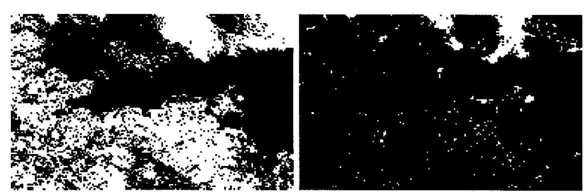


Fig. 4. a) Fig. 4. b)

Figure 4. Example of segment location.

3. A2R2V

In this section, we will present another application of SMA/OODI by describing our raster-scanned color cartographic map interpretation system called A2R2V (***A**nalogical-**to**-**R**aster-**to**-**V**ector*) (see also [4–6, 9]).

3.1 HOW DOES IT WORK?

A2R2V is based on SMA/OODI of color images. SMA/OODI of cartographic images is interpreted as a separate representation of cartographic patterns (alphanumeric, punctual, linear, and area). Our map interpretation system explores the idea of synthesis of invariant graphic images at low-level processing (vectorization and segmentation). This means that we ran vectorization-recognition and segmentation-interpretation systems simultaneously. Although these systems can generate some errors, they are much more useful for the following understanding algorithms and man-machine interaction because of its output in nearly recognized objects of interest.

We began map recognition from global binarization followed by classical OCR-identification with artificial neural networks (ANN), supervised clustering, knowledge-based recognition rules, and morphology-based vectorization. To overcome the problem of labor-intensive training, we designed simplified images. For this purpose, we utilized linear combinations of color components or image representations (*false color technique*) and binary representation composing (*composite image technique*). These techniques are application-independent. However, within the framework of our approach map recognition may be treated as a common (application-dependent) task [17]. We followed the concept that important semantic information necessary to interpret an image is not represented in single pixels but in meaningful image segments and their mutual relationships [1, 4–6, 9, 20].

We set forth a conception of composite image representation and decomposition. The main goal of image decomposition consists of object linking by its associated names. We used image synthesis based on object-fitting compact hierarchical segmentation [16]. We performed composite representations (or simply composites) of the source image by means of a reduced number of color or tone components and segments. In this manner, visually perceived objects are not eliminated and *the image's semantics* is preserved (see Section 2).

Composite images form a book in which objects of interest can be found and recognized on appropriate page(s) [6]. Thus, a page number defines the method of thresholding and certain tuning parameters that can be learned interactively or automatically (Figure 5).

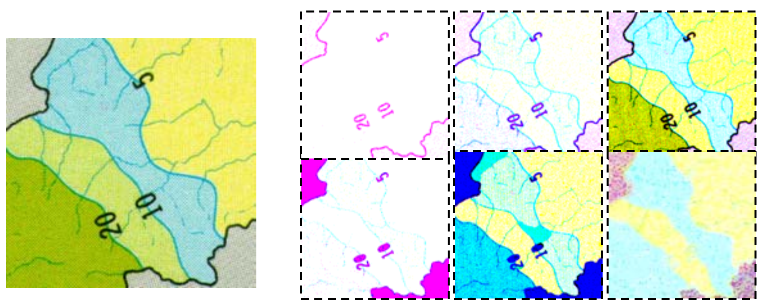


Figure 5: Source image (left) and some pages of a book of composite images (right).

3.2 A2R2V MODULES

Recognition systems of alphanumeric characters, punctual, linear, and area objects are subsequently described in [4–6]. They support segmentation-recognition-interpretation-vectorization modules of A2R2V. Their names rather underline the desire to stratify the map by top-level vector thematic layers (punctual, linear, etc.) than by only recognition and vector points, arcs, etc. maintaining all of these together in one layer. In the following, we shall present the main ideas of the ***Fine-to-Coarse Scale*** (F2CS) method. This method originated from the unsolved problem of vector description of raster objects and the fact that vector data in fine-scale maps are often available. In a certain sense, it represents a promising alternative. The method shows how to use feedback already acquired from semantic information to obtain new information.

Let us suppose that we have a vector cartographic image I_1 (or and already recognized raster image) in scale s_1 of given territory T and a raster cartographic image I_2 of T to be vectored (recognized) in scale s_2 and $s_1 > s_2$ (e.g., s_1 = 1: 100,000 and s_2 = 1: 50,000). Our goal is to use the information from I_1 in vectorization of I_2. Note that I_1 can be considered as generalization[1] of I_2: $I_1 = G(I_2)$, i.e., if an object $O_2 \in I_2$, then there can exist $O_1 \in I_1$ such that $O_1 = G(O_2)$. We denote Ω—the set of all such objects O_2 from I_2 and Θ—the compliment of Ω in I_2: $I_2 = \Omega \cup \Theta$. We also put $\omega = G(\Omega)$ and note that $\omega \subseteq I_1$. Obviously, to vector objects from Ω and Θ we need two different strategies. Objects from Ω can be vectored using features (position, color or colors, shape, etc.) of vector objects from ω. After objects of Ω have been vectored, we can vector objects from Θ by one of the A2R2V modules as new cartographic material. Results of vectorization

[1] We do not discuss here what this generalization is

obtained at each step of this process as well as processing by other A2R2V modules are feedback to reuse in the next step. To perform the F2CS method, we used conceptual clustering [8] based on the set of prescribed object features [4] and the concept of the associated to image function [9]. Note that the method also solves the difficult problem of the search for object to be vectored in the entire raster map field. In this case, a vectored object can be found in the nearest neighborhood of its generalized analog and nowhere else. An example of application of the fine-to-coarse scale method is shown in Figure 6.

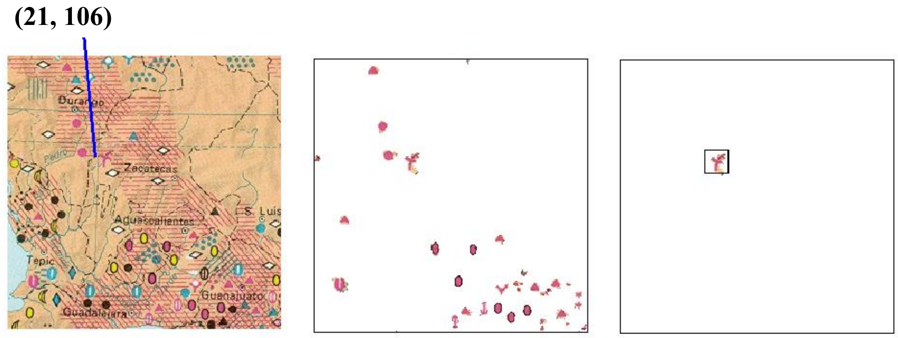
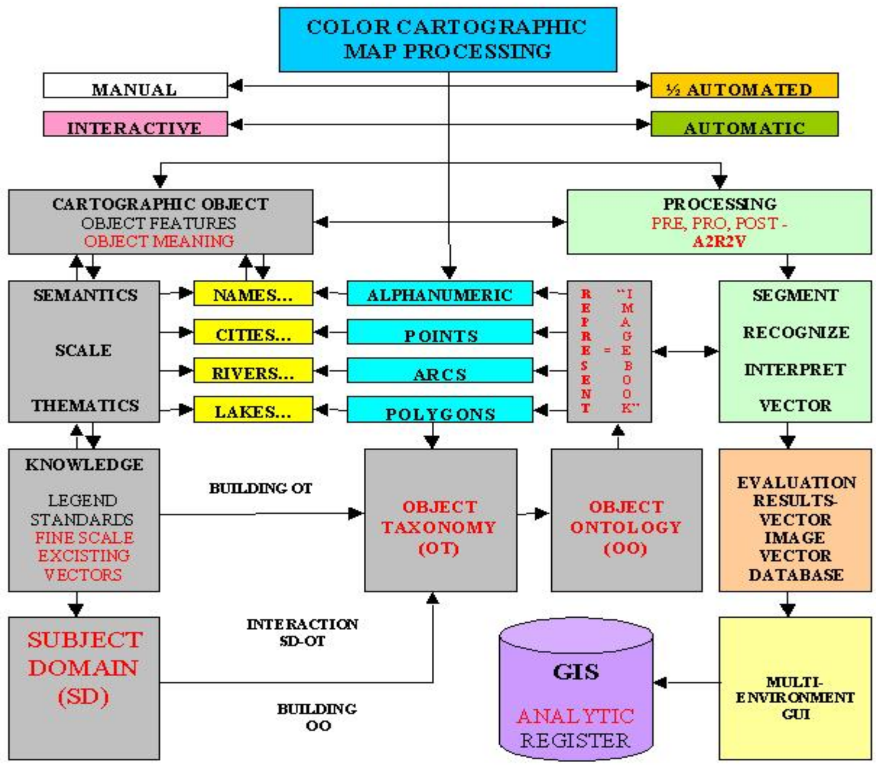


Figure 6: Recognition of punctual cartographic pattern. a) Original image in scale s_1 with input information: there is *near* geographic coordinates (21,106), a pattern denominated *Palm*. b) Image in scale s_2 ($s_2 < s_1$) obtained after application of punctual object recognition with conceptual clustering (criterion: β_o-connected, $\beta_o = 0.9$) [8], considering the associated to the image function restricted to one of the generated groups and adding pixels (region merging) [9]. Note that we searched for the pattern only near and for the already recognized *fine* pattern and nowhere else. c) Recognition of *coarse* pattern (function) Palm.

3.3 OBJECT-ORIENTED DATA INTEGRATION OF GIS-READY INFORMATION

We designated A2R2V as a multi-environment system that does not depend on particular data format and that is oriented to process color raster-scanned images. Its GUI is described as follows: At low level, it has modules of automatic recognition of alphanumeric, punctual, linear, and area objects in raster-scanned color cartographic images that have been programmed in C. Thus, a database with quantitative, qualitative, and nominal features is associated with each recognized visual object. At the intermediate level, a Java module supports correct conversion of corresponding database to be processed at high level in one of the environments: Unix; Linux, or Windows. Therefore, the user of the system should not seek unified or particular representation of spatial databases in an environment, but only chooses the most convenient representation of the three provided. We are now developing a decision-making tool to support most adequately the particular GIS-application of the user's choice.



Flow chart 2: A2R2V functioning (components, modules, and interaction)

3.4 SUMMING UP

Now we shall explain the content of Flow chart 2 that summarizes our approach to color cartographic image raster-to-vector conversion. Our comments are as follows.

1) Any map interpretation system deals with processing of alphanumeric, punctual, linear, and area raster objects. The majority of state-of-the art systems based on image processing and graphic recognition [7, 11−15] consider color, shape and texture components of the concept of cartographic objects, usually omitting the meaning and topology. Of course, color, shape, etc., are important cues. However, they are only cues: there is no pure color in raster-scanned maps. What is the shape of the raster object; what is the arc centerline? In contrast, our definition of spatial semantic object (cartographic pattern) includes the following components:

   Cartographic pattern = (*color* <*space*>; *geometry* <*location, shape, etc.*>; *topology* <*point, arc, area, etc.*>, *and attribute* <*e.g., name of object; etc.*>).

   This definition allows full use of the peculiarities of very cartography for GIS-ready information integration. Additional arguments may be found in [1, 4–6, 9, 16, 20].

2) Moreover, the majority of contemporary systems are pixel-oriented. They are artificial and destroy most essential image characteristics §1. Increasingly complex algorithms for machine recognition of maps that do not materially improve the results. We believe that the most effective image formats preserve natural image structure and thus provide OODI. This thesis is especially true for cartographic images that because they are intermediate between man-made drawings and natural images provide a nearly ideal model for semantic analysis; OODI is quite natural here within the context of GIS [6, 20]. This leads to natural taxonomic classification of cartographic patterns, the definition of cartographic subject domain (SD) (a set of names) dependent on map thematic, scale, legend, toponyms, and a priori knowledge concerning the map (existing/reworked vectors in fine scale). Different sources of evidence can be also put into SD to support efficient map processing. Interaction between SD and object taxonomy (OT) has led to conceptual structuration of cartographic data in hierarchical object ontology (OO) (nodes of OO are concepts—not words). Thus, we are looking for correct and adequate representation of raster objects as a thematic image book *prior to* processing/conversion. However, results of processing can be feedback and correct §3.2. In Flow chart 2, blocks in gray with text in red illustrate our system approach.

3) With regard to automatic interpretation of color cartographic images, this presents certain difficulties for state-of-the art image processing, pattern recognition, and artificial intelligence. The set of vector maps that one can expect as an output of such an interpretation is very useful for GIS, new map production, and old map updating. However, it appears unrealistic to obtain a fully automatic computer-based interpretation system free of errors [4–6, 9, 11–15]. Additionally, please note that high efficiency of interpretation is required for vector map production and updating first. It appears reasonable to obtain in both cases 90–95% successfully recognized objects. This is to avoid excessive work on corrections of errors produced by the computer system, which can sometimes be greater than manual raster-to-vector conversion [19]. Within the framework of our approach, manual, interactive, semi-automated, and automatic processing may prove useful. Our point is: *Apply them application-dependently, use sources of evidence to respond alarms* [4–6, 9].

In this section, we presented a system for automatic interpretation of raster-scanned color cartographic maps. The highlight of our system is two intelligent color image segmentation techniques. These allow searching for names of processed sets of pixels. Segmented and recognized objects are subsequently vectored to be finally included in GIS. These three stages (segmentation-recognition-vectorization) are Object-oriented data integration to GIS or GIS-ready information [18]. In our experiments, we used complex, full-size, raster-scanned color cartographic images with promising results [4–6, 9, 16].

4. CONCLUSION

We illustrated SMA/OODI by describing *Analysis* system and color cartographic map interpretation system (*A2R2V*) that encapsulate basic elements of SMA/OODI. Application of SMA/OODI for A2R2V allows increasing this system efficiency within the general context of raster-to-vector automatic conversion. Note that the latter problem is very complex and has attracted much attention during the last few decades. However, to date there is a lack of satisfactory solution of this problem. From our point of view, the proposed alternative is promising.

We attempted to demonstrate that a system, semantic-based approach to the raster-to-vector problem can be fruitful. Within the context of the A2R2V system this means, first, decomposition of source image by multiple semantic hierarchical networks. Second is segmentation with mutual recognition of appropriate primitives, while third is development of a unified, knowledge-based learning and self-learning system with optimal human-machine interaction. Our research is concerned with this approach.

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