INTELLIGENT SEGMENTATION IN THE TASK OF RASTER-TO-VECTOR CONVERSION OF COLOR CARTOGRAPHIC IMAGES

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Abstract

We present an approach to a raster-to-vector conversion of color cartographic images. This is simultaneous segmentation-recognition-interpretation system when successfully segmented objects of interest (alphanumeric, punctual, linear, and area) are labeled by the system in the same, but are different for each type of objects, gray-level values. We call it the composite image technique. We exchange the source image by a number of composite image representations. Every composite image representation is associated with certain feature. Some of the composite images that contain the objects of interest serve to be used in the following object detection-recognition-interpretation. The specification of features associated with perspective composite representations is regarded as a type of knowledge domain. The results of gray-level color image conversion are presented.

Key words: Raster-to-Vector Conversion, Image Segmentation and Representation, Image Recognition, Image Segments Hierarchy, Image Synthesis

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1. Introduction.

Segmentation is fundamental to the field of image processing because it is used to provide the basic representation on which understanding algorithms operate. This is especially true for the task of raster-to-vector conversion systems. The ability to build up a representation from individual pixels of a scanned image, which exploits relationships such as local proximity and highlights the structures of the underlying components, is important for the extraction of features during interpretation and recognition [1]. In general, the nature of this representation is application dependent. In the present work, we developed an application independent segmentation.

Up to the now a great variety of segmentation algorithms for gray-level images has been proposed. The majority of color segmentation approaches is based on monochrome segmentation approaches operating in different color spaces [8]. Gray level segmentation methods can be directly applied to each component of a color space; thus, the results can be combined in some way to obtain a final segmentation result. However, one of the problems is *how to employ the color information as a whole for each pixel.* When the color is projected onto three *RGB* color components, the color information is so scattered that the color image becomes simply multispectral image and the color information that humans can perceive is lost [13]. Another problem is *how to choose the color representation for segmentation* [2,8]. There is no single color representation that can surpass others for segmenting all kinds of color images. The use of nonlinear spaces, such as *HSI* and the normalized color space can solve the problem to certain approximation. However, the nonlinear spaces have essential, non-removable singularities and there are spurious modes in the distribution of values [14].

An alternative solution presented in this work is invariant image representation (composite images, or simply *composites*) that does not depend on choice of particular color space. The processing of a color image is individual segmentation by each color component into image meaningful (or invariant with respect to a given, unnecessary color feature) regions, first and, then – image's integrated segmentation-recognition (or "objects of interest designing"). Moreover, the prescribed set of features is regarded as a type of *knowledge domain.*

The *composite image technique* includes object-fitting compact hierarchical segmentation, binarization of segmented images, and synthesis of binary representations. The main goal of image synthesis consists of the object linking by its associated names.

In the following sections, we build up composite image representations based on object-fitting compact hierarchical segmentation [3-6].

2. Object-fitting compact hierarchical segmentation.

Object-fitting compact hierarchical segmentation [3,4] is a sequence of embedded partitions without repetition of composed segments in different partitions (Fig. 1).

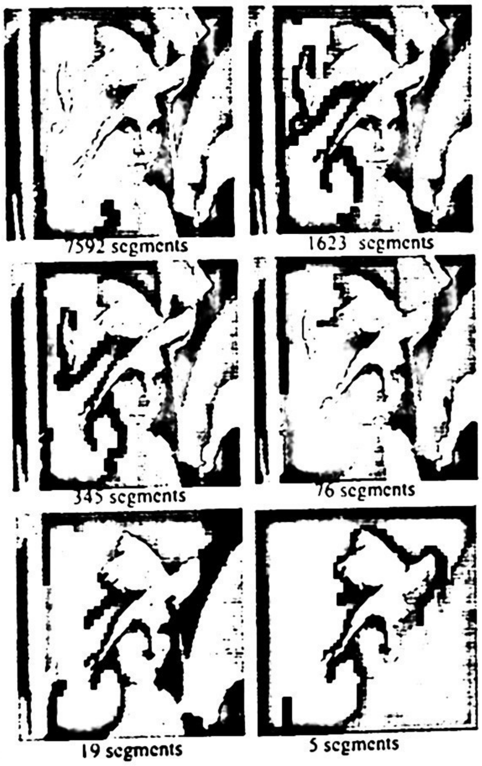

Fig. 1. Compact hierarchical image segmentation

A partition is obtained by iterative segment splitting or merging. In the merging mode, any segment in each iteration merges into the nearest adjacent segment. Number 2^i bound total number of segments, where i is the number of iteration.

Number of segments N has to be taken into account for automatic color image analysis. Indeed, the merging of segments into objects defines the *image semantics*.

This number decreases approximately as $(4 \div 5)^{-i}$, where i is the iteration number (Fig. 2). From our point of view, deviation from this exponential dependence leads to semantics violation. Disclosed regularity can be useful for automatic analysis of gray-scale and color images.

Our experiments have shown (Fig. 2a) that the compressed volume of an image is decreased in the same exponential mode (image compression with information-lossless standard algorithms: RAR, LZH, etc.). Eliminating the dependence on iteration number i, we can obtain the exponent-mode relation of compressed data volume V on number of segments N as follows:

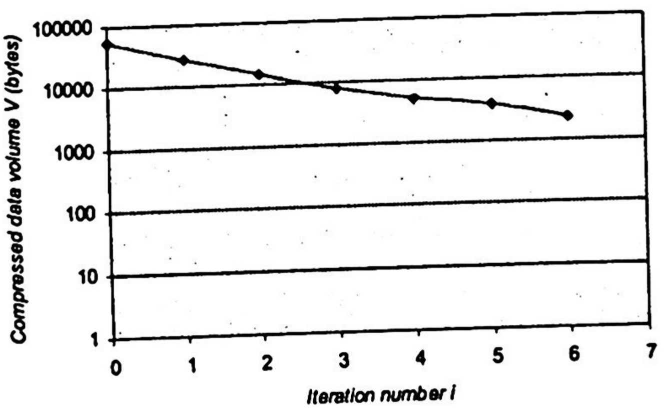

Fig. 2a. Linear dependence of compressed image volume on iteration number i (in experiments carried out by A. Zaitseva (SPIIRAS))

$$N/N_0 = (V/V_0)^{\alpha}$$

Where N_0, V_0 denote number of segments and compressed volume of the source image respectively; α is some real coefficient.

We obtained that in the case of object-fitting compact hierarchical segmentation (Fig. 1) the exponent α is approximately *2.9*. Note that for non-adaptive pyramid segmentation [2], α is approximately *1.4*.

It is known that the volume of compressed data is closely related to the *amount of information into data*. Thus, a theoretical explanation of the obtained experimental dependencies (Figs. 2 and 2a) represents an interesting research topic of Pattern Recognition.

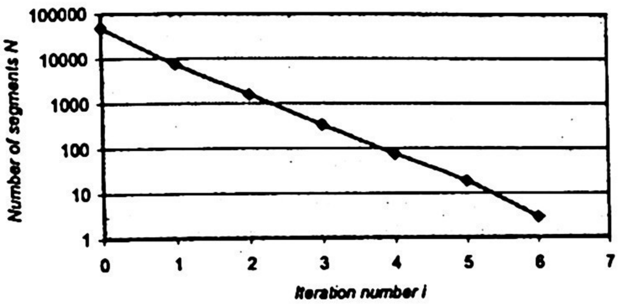

Fig. 2. Linear dependence of number of segments N on iteration number i (in experiments carried out by H. Rumbo (CIC))

3. Composite image representation.

We have found that in addition to natural decomposition (e.g., R, G or B – component splitting) of color images, artificial representations can also be useful for objects of interest detection-recognition [5,6]. Our approach provides composite representations of the source image by means of reduced number of color or tone components and segments. Composite image representation is a sequence of binary representations, which are packed into different bit planes. These binary images are the result of two-valued classification of source image by some feature (intensity, area, invariant moments, etc.).

A bit component of composite image (Fig. 3) computes by means of thresholding of the current segmented image. The threshold is equal to the average all over image of intensity, geometric or otherwise (features), e.g., $I^{(i)}$. To threshold the image, $I^{(i)}$ is compared with its average over pixels of each segment, e.g., $I^{(s)}$ as follows: $I^{(i)} \geq (<) \ \xi \ I^{(s)}$, where ξ is a tuning parameter.

By substitution of intensity feature with any other feature (pixel number, segment linear dimension, orientation angle, etc.; see Section 6), we can obtain another composite representations which are useful for detection of polygons, contour, noises, etc. Examples of composite image representations are shown in Fig. 3a.

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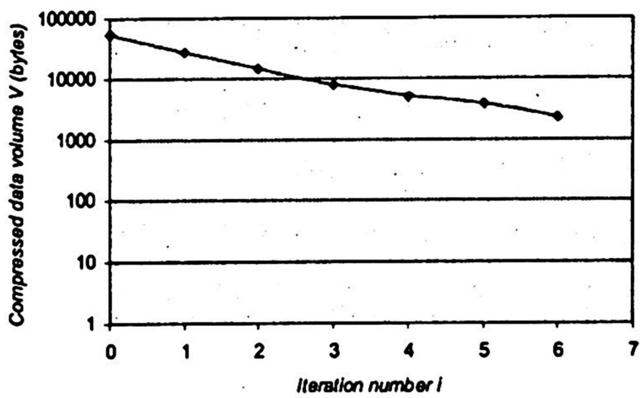

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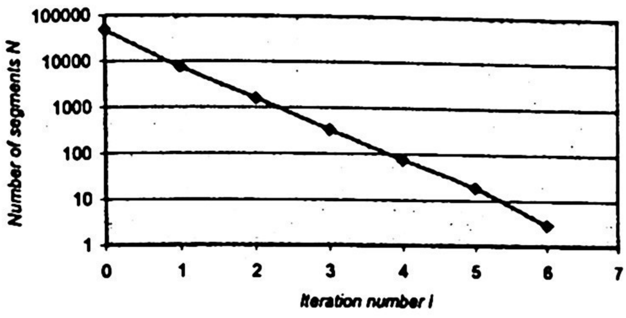

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Fig. 3. Bit components of composite images obtained by means of thresholding of Lena's source and segmented images

Fig. 3a. Composite image representations

The first representation of Fig. 3a is obtained from the Lena source image by means of intensity thresholding. As a rule, sharpness is achieved for this composite image. Other composite images of Fig. 3a are obtained with different values of the tuning parameter ξ from the images of Fig. 1. To compose these images, we also used the geometric features from the feature set (Section 6) in addition to intensity feature.

The bit components are packed in the resulting representation, where the extrema of intensity indicate the pixels associated with unchanged binary feature.

Essentially, the composite images form a "book" in which the objects of interest can be found on appropriated page(s). Thus, a "page number" defines the method of thresholding and the tuning parameter ξ.

4. Color composites.

Compact hierarchical segmentation of a color image is performed by each independent color components (R, G, and B) considering these as semi-tone images. In this way, coinciding intensities of resulting R, G, and B composite images indicate the segments of equal color with respect to using feature. This can be used for invariant color image description.

As a rule, compact hierarchical image segmentation implies that color segments are enlarged simultaneously in accordance to regularities presented in Section 2. Due to the self-consistence of *RGB*-segmentation behavior, visual quality improvement in composite intensities becomes available (Fig. 4).

The method requires significant operative memory space. To overcome this disadvantage, we used special data organization in the form of irregular dynamic trees [3,4], that provides optimal in memory space computing for the successive scanning of image scales. Due to data organization, a practical use of our program package does not require further algorithmic development. The user needs only to make adequate choice to carry out task features from prescribed feature set (the *knowledge domain*).

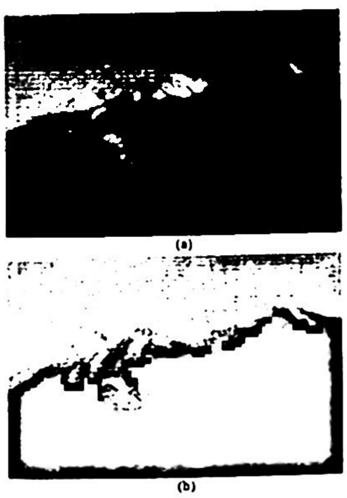

Fig. 4. Image enhancement with composites: (a) source and (b) composite image

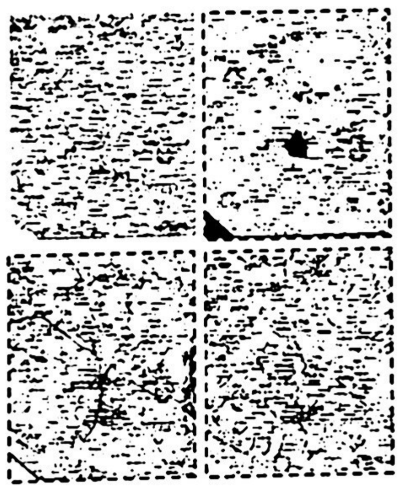

Fig. 5. Cartographic pattern retrieval from a color map image 1082x1406 pixels (upper left corner)

5. Applications of composites.

Image two-valued classification (binarization) is one of the most important tasks in modern recognition methods. In the frameworks of the composite image technique, we obtained a few solutions for this task [3-6]. By applying composites, we are able to extract cartographic data using *R*, *G*, and *B*-components of full-size color raster-scanned image (Fig. 5).

Fig. 6 shows how our method insures object detection in the task of recognition of inclined digits embedded in graphics. This illustrates that each composite image contains machine-treatable bit-planes for target object detection and also purposeless bit-planes. Indeed, to effectively recognize the objects of interest, it is better to search these objects on appropriated bit-planes.

Although, our system can generate some errors in interpretation, it is much more useful for the following understanding algorithms because its output is nearly recognized objects of interest.

Owing to use the geometric features in addition to intensity feature, our method detects hidden for other methods image "technological history", i.e., how the image was drawn and printed (Fig. 7).

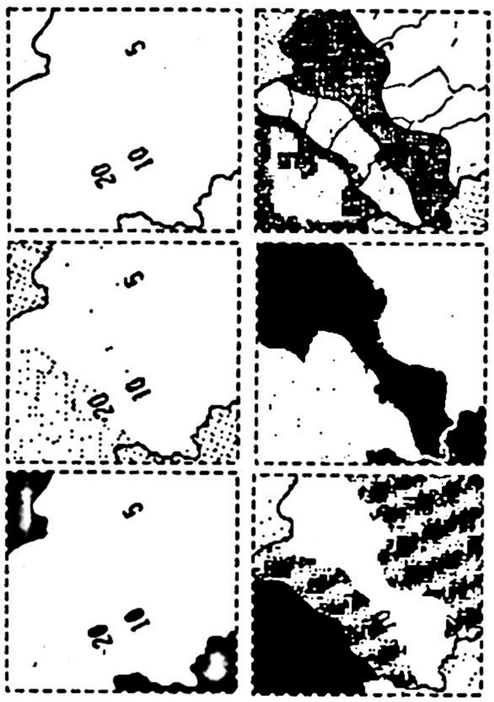

Fig. 6. Bit-planes suitable for digit recognition (left aligned) and other purposes (right aligned)

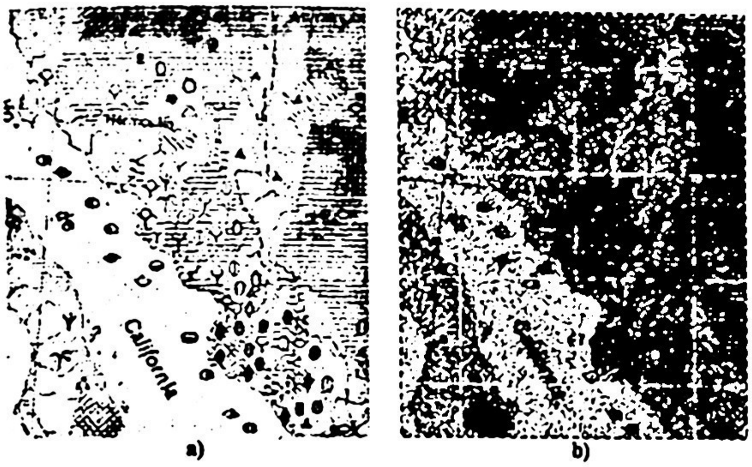

Fig. 7. Hidden network pattern reveal: (a) source and (b) composite image

6. Comments.

In previous sections, the details of the composite image technique have been described for very first time. Presented approach exploits the user's experience providing the knowledge domain in the form of the prescribed feature-attribute set. This set contains a number of attributes and numerous features. The attributes are a primary set of segment characteristics estimated and dynamically stored for all image segments at any level of the composite image representation. This provides a full-value use of object-fitting hierarchical segmentation. The features are numerical segment characteristics, which are obtained as output of data conversion, and are selected in function of the processing stage and the problem context. Thus, prescribed segment attributes are the following:

1. Extrema of numerical characteristics
   - Global (for the whole image);
   - Local (for a neighborhood of the segment).
2. Additive
   - Integral intensity (the sum of pixel intensities);
   - Number of pixels;
   - Integral first and second moments computed with respect to the origin.
3. Non-additive perimeter.
4. Description of the adjacent segments in terms of binary relationships.

These data provide an estimation of the intensity and geometric segment features: pixel intensity range, average intensity, invariant moments, parameters of linear sizes and shapes, etc. In this manner, the features used in generation of object-fitting hierarchy of the segments can be different from the features used in object recognition [3,4]. As a rule, at first step of image treatment, only intensity features are useful, because the source image pixels do not form geometrically meaningful segments and objects. Consequently, up to reaching image invariant representation other features are used for object designing and recognition. Moreover, the image composite representation with respect to a given feature means the recognition of "corresponding" to this feature, objects of interest.

The method has numerously been tested on complex raster-scanned color cartographic and semi-tone images rendering good results [6].

To our knowledge, this is one of the first attempts to design a segmentation-recognition computer system for complex color images of arbitrary type [7-10].

7. Conclusions.

The problem of *how and to what degree the semantic information should be employed in image segmentation* has led us to novel conception of composite image representation for mutual object detection-recognition at low level processing. We conjecture that modern segmentation systems must support mutual object detection-recognition-interpretation, starting at low-level, memorizing results at the intermediate level, and effectively communicating these results to the high level. The approach proceeding from this conjecture is called *composite image technique*. The idea is to prepare the source image as much as possible for subsequent high- level processing of image regions. In most of the existing color image segmentation approaches, definition of a region is based on similarity of color. This assumption often makes it difficult for any algorithms to separate the objects with highlights, shadows, shadings or texture, which cause inhomogeneity of colors of the object's surface. Using *HSI* can solve this problem to some extent, except that hue is unstable at low saturation. Some physics-based models have been proposed to solve this problem [8,9]. These models take into account the color formation, but they have too many restrictions, which prevent them from being extensively applied. Homogram thresholding and fuzzy logic algorithms applied to the problem have also exhibited limitations [11,12].

We saw an alternative solution of the problem defining image regions by additional *quantitative, qualitative, and nominal features* (in addition to color feature), which on the whole render the *user's knowledge domain*. We think that this is a kind of advanced simulation of the human's visual perception. However, it is necessary to emphasize that for optimization of labor-intensive program training a strong formalization of composite image technique is now required. We are under way to solve this problem.

In our experiments, we used between others, complex raster-scanned color cartographic images, which being intermediate between drawings and natural images provide a nearly ideal model for testing because they have characteristics of both [6]. We obtained promising results in this *subject domain*.

At the same time, automatic interpretation of color images presents certain difficulties for state-of-the-art in image processing and also artificial intelligence. To date, it appears unrealistic to obtain fully automatic computer-based interpretation system free of errors [8,10].

We believe that only integrated approach to the problem can be fruitful. In the context of the present work, this means first, decomposition of source image by multiple hierarchical components to achieve a stable, accurate representation in the presence of degraded images. Second is the segmentation with mutual recognition of appropriate primitives. Finally, there is the development of a unified knowledge-based trainable and self-trainable system with optimal human-machine interaction for color image treatment. Our future research will be concerned with this approach.

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