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Color image segmentation: Rough-set theoretic approach

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Abstract

A new color image segmentation algorithm using the concept of histon, based on Rough-set theory, is presented in this paper. The histon is an encrustation of histogram such that the elements in the histon are the set of all the pixels that can be classified as possibly belonging to the same segment. In rough-set theoretic sense, the histogram correlates with the lower approximation and the histon correlates with upper approximation. The roughness measure at every intensity level is calculated and then a thresholding method is applied for image segmentation. The proposed approach is compared with the histogram-based approach and the histon based approach. The experimental results demonstrate that the proposed approach yields better segmentation.

Keywords: Segmentation; Rough set; Histon; Histogram

1. Introduction

Image segmentation is one of the most challenging tasks in image processing and is a very important pre-processing step in the problems in the area of image analysis, computer vision, and pattern recognition (Cheng et al., 2001; Liew et al., 2005). In many applications, the quality of final object classification and scene interpretation depends largely on the quality of the segmented output (Pal and Pal, 1993). In segmentation, an image is partitioned into different non-overlapping homogeneous regions, where the homogeneity of a region may be composed based on different criteria such as gray level, color or texture.

While segmenting a monochrome image, a common problem arises when an image has a background of varying gray levels such as gradually changing shades. This problem is inherent since intensity is the only available information. It is well known that humans can discern only a less than two dozen gray levels, whereas they can distinguish amongst thousands of colors. Therefore the objects that cannot be usually extracted using gray levels can be easily extracted using color information. The information content in the color is huge and therefore color image segmentation assumes importance in pattern recognition and computer vision applications. The applications of color image segmentation include medical image diagnostics, video object segmentation; object based video compression, object detection from remotely sensed images, and many more.

The research in this area has led to many different techniques, which can be broadly classified into histogram based, edge based, region based, clustering, and combination of these techniques (Aghbari and Al-Haj, 2006; Cheng and Li, 2003). Large number of segmentation algorithms is present in the literature, but there is no single algorithm that can be considered good for all images (Pal and Pal, 1993). Algorithms developed for a class of images may not always produce good results for other classes of images. The advantages and disadvantages of these techniques have been discussed in (Cheng et al., 2001).

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One of the most widely used techniques for image segmentation is the histogram-based thresholding, which assumes that homogeneous objects in the image manifest themselves as clusters. The advantage of such methods is that they do not need any a priori information of the image (Liu and Yang, 1994). These methods are based only on gray levels and do not take into account the spatial correlation of the same or similar valued elements. However, real-world images usually have strong correlation between neighboring pixels. Adjacent pixels in an object are generally not independent of each other. To overcome this drawback, Cheng et al. (1998, 2002) used the fuzzy homogeneity approach in which the concept of homogram was introduced. Homogram extracts homogeneous regions in a color image. The homogram of an image is constructed by considering the absolute difference between intensity values of the pixel and the neighborhood pixels. However, this method takes into account only the spatial correlation of a pixel with neighboring pixels in the same image plane and it does not consider the correlation amongst pixels in the other color planes.

Mohabey and Ray (2000a,b) introduced a concept of histon, which is a contour plotted on the top of the histogram by considering a similar color sphere of a predefined radius around a pixel. The concept encapsulates the fundamentals of color image segmentation in a rough-set theoretic sense. The base histogram is considered as the lower approximation and the histon as upper approximation. The upper approximation is a collection of all points, which may or may not belong to one segment but certainly share a unique property that the elements have similar colors. For segmentation, only the upper approximation is considered and the histogram-based segmentation technique is applied on the histon to find the different regions in the image. The method does not take into account the lower approximation for segmentation and thus fails to utilize the properties of the boundary region between the two approximations in segmentation.

In this paper, we propose a segmentation scheme that uses the roughness measure of the rough-set as a basis for segmentation to overcome the drawback. Roughness index is large where the number of elements with similar color is large compared to the number of elements having same color. The index is small when number of elements having similar color is slightly greater than or equal to the number of elements with same color. Clearly, the index will be very small in the boundary between two objects and it will be large in the object region. We have used this property of the rough-set theory to achieve better segmentation results.

The paper is organized as follows: in Section 2, we present the rough-set theory and properties of rough set. In Section 3, we describe the concept of histon and calculation of roughness measure. Section 4 describes segmentation algorithm and experimental results are given in Section 5, followed by concluding remarks in Section 6.

2. Rough-set theory and properties

We present some preliminary concepts of rough-set theory that are relevant to this paper. According to the definition given by Pawlak (1991), an information system is a pair $S = \langle U, A, V, f \rangle$ or a function $f: U \times A \to V$, where U is a non-empty finite set of N objects $\{x_1, x_2, \ldots, x_N\}$ called the universe, A is a non-empty finite set of attributes, and V is a value set such that $a: U \to V_a$ for every $a \in A$. The set V_a is the set of values of attribute a, called the domain of a. A subset of attributes $B \subseteq A$ defines an equivalence relation (called an indiscernibility relation) on U. This relation is defined as

$$\mathrm{IND}(B) = \{(x, y) \in U \times U : \text{for every } a \in B, a(x) = a(y)\} \tag{1}$$

The elements of U that satisfy the relation $\mathrm{IND}(B)$ are objects with the same values for attributes B and therefore they are indiscernible with respect to B. $U/\mathrm{IND}(B)$ denotes the set of equivalence classes of $\mathrm{IND}(B)$. The equivalence classes of $\mathrm{IND}(B)$ are called basic categories (concepts) of the knowledge B.

Given any subset of attributes B, any concept $X \subseteq U$ can be defined approximately by employing two exact sets called lower and upper approximations. The lower and upper approximations can be defined as follows:

$$\overline{B}X = \cup\{Y \in U|\mathrm{IND}(B) : Y \cap X \neq \phi\} \tag{2}$$

$$\underline{B}X = \cup\{Y \in U|\mathrm{IND}(B) : Y \subseteq X\} \tag{3}$$

The set $\underline{B}X$, also known as B-lower approximation of X, is the set of all elements of U which can be classified as elements of X with certainty, in the knowledge B. The set $\overline{B}X$, also known as B-upper approximation of X, is the set of elements of U which can possibly be classified as the elements of X, employing knowledge B. Obviously, the difference set yields the set of elements which lie around the boundary.

The set $BN_R(X) = \overline{B}X - \underline{B}X$ is called the B-boundary of X or B-borderline region of X. This is the set of elements, which cannot be classified to X or to $-X$ using the knowledge B. The borderline region actually represents the inexactness of the set X with respect to the knowledge B. The greater the borderline region of the set more is the inexactness. This idea can be expressed more precisely by the accuracy measure defined as

$$\alpha_B(X) = \frac{|\underline{B}X|}{|\overline{B}X|} \quad \text{for } X \neq \phi \tag{4}$$

where $|\cdot|$ is the cardinality operator. The accuracy measure captures the degree of completeness of the knowledge about the set X. Here, we can also define a measure to express the degree of inexactness of the set X, called roughness measure or roughness index of X or B-roughness of X, given by

$$\rho_B(X) = 1 - \alpha_B(X) \tag{5}$$