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Segmentation of color images using a linguistic 2-tuples model

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ABSTRACT

In this paper we address the problem of color image segmentation transforming it into a decision making paradigm. A set of experts is provided, so that each expert assigns a preference degree of each pixel to every object of the image considering also the ignorance associated with such assignation. We represent the objects by means of fuzzy linguistic labels and using the decision-making model based on 2-tuples we apply an aggregation phase to classify each pixel. To obtain the segmented image we consider the preference values associated with a pixel and also with its neighbors. We test our segmentation method on Berkeley segmentation database [21] and we compare the experimental results with the ones obtained by FCM method [4] and MAP-ML method [17].

1. Introduction

Image segmentation is the process of partitioning an image into disjoint and homogeneous regions (subsets of pixels) [35]. It plays a key role in many computer vision applications such as scene analysis, image retrieval and pattern recognition [1,32,34,47]. This is one of the most difficult processes in image processing since it determines to a large extent the results in the aforementioned applications.

Most of segmentation methods in the literature can be classified as edge-based methods [2] or region-based methods [22,40]. The former try to find the boundaries of the objects in the image while the latter separate an image into several homogeneous regions. Classical edge-based methods are easy to get trapped in local minima and are sensitive to the initial curve, so nowadays researchers are devoted to study region-based methods [23]. In this work we study a new region-based segmentation method based solely in the color of each pixel.

There are many segmentation techniques in which each pixel is assigned to a unique region; that is, regions are defined in a crisp way [16,19,33]. Nevertheless, in real images and due to low resolution, uneven illumination and scale changes, it is necessary to provide to each pixel a membership degree to a region. In most of color segmentation algorithms the belonging of a pixel to a region is based on the color characteristics of the image represented in a color space. The assumption of using color similarity makes it difficult for any algorithm to separate the objects, because of the previously cited problems and the non-homogeneity of colors in the image objects. Bearing in mind all these considerations, the use of fuzzy techniques have provided very appropriate solutions [14,29,36,38,41].

In this paper, we introduce a new color image segmentation algorithm using fuzzy techniques. The novelty of the proposed work is to convert an image segmentation problem into a decision-making problem. We provide different experts,

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by means of different membership functions, so that each expert assigns to each pixel a preference degree to every object of the considered image. Representing the objects by means of fuzzy linguistic labels and using the decision-making model based on 2-tuples, we apply the aggregation phase of a decision-making approach to classify each pixel. In this phase, considering the preference values associated with a pixel and with its neighboring ones, we obtain the segmented image.

Finally, we present an experimental study with a set of color images comparing the results obtained by our approach and the results obtained by other proposals of the literature [4,17].

The paper is organized as follows. Section 2 recalls some basic concepts. In Section 3 we present the algorithm for image color segmentation, explaining in detail each of its steps. In Section 4 we show the results obtained with our proposal and a comparison with other approaches. Some conclusions are raised in Section 5.

2. Preliminary definitions

In this section we recall some well-known definitions and results used throughout the paper.

A triangular norm (t-norm for short) T: $[0,1]^2 \to [0,1]$ is an associative, commutative, increasing function such that $T(1, x) = x$ for all $x \in [0,1]$. The three basic t-norms are: the minimum $T_M(x, y) = \min(x, y)$, the product $T_P(x, y) = x \cdot y$ and the Łukasiewicz $T_L(x, y) = \max(x + y - 1, 0)$.

A function c: $[0,1] \to [0,1]$ such that $c(0) = 1$, $c(1) = 0$ that is strictly decreasing and continuous is called strict negation. If, in addition, c is involutive, then it is said that it is a strong negation.

Concerning aggregation functions, we will follow the approach and definition given by [9], see also [3,12,28]. An aggregation function of dimension n (n-ary aggregation function) is a mapping $\mathcal{M} : [0, 1]^n \to [0, 1]$ such that

(1) $\mathcal{M}(x_1, \ldots, x_n) = 0$ if and only if $x_1 = \cdots = x_n = 0$;
(2) $\mathcal{M}(x_1, \ldots, x_n) = 1$ if and only if $x_1 = \cdots = x_n = 1$;
(3) $\mathcal{M}$ is non-decreasing.

The concept of restricted equivalence function [5] arises from the concept of equivalence [18] and from the properties usually demanded to the measures used for comparing images [6,7,13,43,44]. In [8], the authors apply restricted equivalence functions to the computation of the threshold of a gray scale image.

Definition 1. A function REF: $[0,1]^2 \to [0,1]$ is called restricted equivalence function associated with the strong negation c, if it satisfies the following conditions:

(1) $REF(x, y) = REF(y, x)$ for all $x, y \in [0,1]$;
(2) $REF(x, y) = 1$ if and only if $x = y$;
(3) $REF(x, y) = 0$ if and only if $x = 1$ and $y = 0$ or $x = 0$ and $y = 1$;
(4) $REF(x, y) = REF(c(x), c(y))$ for all $x, y \in [0,1]$, c being a strong negation;
(5) For all $x, y, z \in [0,1]$, if $x \leqslant y \leqslant z$, then $REF(x, y) \geqslant REF(x, z)$ and $REF(y, z) \geqslant REF(x, z)$.

Next, we recall a construction method of REFs from automorphisms. An automorphism of the unit interval is a function φ: $[0,1] \to [0,1]$ that is continuous and strictly increasing, such that $\varphi(0) = 0$ and $\varphi(1) = 1$.

Proposition 1. *If φ_1, φ_2 are two automorphisms of the unit interval, then,*

$$REF(x,y) = \varphi_1^{-1}(1 - |\varphi_2(x) - \varphi_2(y)|) \quad \text{with } c(x) = \varphi_2^{-1}(1 - \varphi_2(x))$$

is a restricted equivalence function.

Proposition 2. *In the conditions of* Proposition 1

$REF(1, x) = x$ for all $x \in [0,1]$ if and only if $\varphi_1(x) = \varphi_2(x)$ for all $x \in [0,1]$.

In [11] it is defined the concept of ignorance function to determine a threshold to binarize an image. These functions are used to measure the degree of ignorance when assigning punctual values as membership degrees of a pixel to the fuzzy set [49] representing the background and to the fuzzy set representing the object.

Definition 2. IG: $[0,1]^2 \to [0,1]$ is called an ignorance function if it satisfies the following conditions:

(1) $IG(x, y) = IG(y, x)$ for all $x, y \in [0,1]$;
(2) $IG(x, y) = 0$ if and only if $x = 1$ or $y = 1$;
(3) If $x = 0.5$ and $y = 0.5$, then $IG(x, y) = 1$;
(4) IG is decreasing in $[0.5,1]^2$;
(5) IG is increasing in $[0,0.5]^2$.