Geometrical and Topological Informations for Image Segmentation with Monte Carlo Markov Chain Implementation

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Abstract

Image segmentation methods based on Markovian assumption consist in optimizing a Gibbs energy function which depends on the observation field and the segmented field. This energy function can be represented as a sum of potentials defined on cliques which are subsets of the grid of sites. The Potts model is the most commonly used to represent the segmented field. However, this model only expresses a potential on classes for nearest neighbor pixels. In this paper, we propose the integration of global informations, like the size of a region, in the local potentials of the Gibbs energy. To extract these informations, we use a representation model well known in geometric modeling: the topological map. Results on synthetic and natural images are provided, showing improvements in the obtained segmented fields.

1 Introduction

The main objective of image segmentation methods is to find areas of homogeneous pixels. In such context, there are two main research axes: the boundary and the region based methods [1]. Fusions of both approaches have also been proposed. Nevertheless, either you are using one approach or the other, a partitioned image is the result of the segmentation operation. This partition is composed of subsets called "classes" for a set of homogeneous pixels, and "regions" for a set of homogeneous and related pixels.

The interest in such treatment can be found in many applications like image compression [2], biomedical image analysis [3, 4],...

For two decades, Monte-Carlo Markov Chain (MCMC) methods have received a increasing interest [5, 6]. This is due to a rigorous mathematical background and the growing power of computers. Since the works of Geman & Geman on image restoration [7], these methods have been applied successfully to image segmentation using different implementations, *i.e.* using stochastic or deterministic algorithms [8, 9].

In such approaches, the image is considered as a hierarchical field composed by an observation field and a segmented or label field. Various parametric models have been proposed to represent the textures of the observation field [10, 11]. But in most cases, the commonly used Potts model [12] is proposed to represent the label field. This model only takes into account the label values of the nearest neighbors in the Gibbs energy function. Geman & Geman [7] tried to add more informations to the Potts model using boundaries estimated during the optimization process. Some boundary configurations were penalized. In [13], this idea has been extensively used. A drawback can be found to this approach in the sense that *a priori* weighted values were given to each boundary configurations.

In this paper, we propose to add informations about the label field's geometry and topology to the energy function. These informations, such as the form or size of a region, would be considered as "global", as opposed to "local" informations provided by the Potts model. Of course, the Potts model will be still used because of its regularization effect, but potentials functions taking into account "global" informations will be added to the Gibbs energy function.

To get these additional informations, we propose the use of a combinatorial model: the topological map [14]. This structure encodes an efficient way all topological and geometrical informations contained in the image. In a sense, topology can be seen as the representation of structural relationships between regions, for instance adjacency. These relationships can be used to characterize a region and, furthermore, a set of regions.

Our segmentation algorithm consists in two steps and is unsupervised considering the number of classes and the model parameters. A first step allows to estimate the number of classes and the model parameters of a Gaussian mixture using a Stochastic Expectation Maximization (SEM) algorithm [15, 16]. During the second step, a Simulated Annealing (SA) based method is applied in order to obtain the final label field. This is the step in which we will introduce topological or geometrical informations extracted from the topological map.