Chapter IV

A Graph-Based Image Segmentation Algorithm Using a Hierarchical Social Metaheuristic

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ABSTRACT

This chapter proposes a new evolutionary graph-based image segmentation method to improve quality results. Our approach is quite general and can be considered as a pixel- or region-based segmentation technique. What is more important is that they (pixels or regions) are not necessarily adjacent. We start from an image described by a simplified undirected weighted graph where nodes represent either pixels or regions (obtained after an oversegmentation process) and weighted edges measure the dissimilarity between pairs of pixels or regions. As a second phase, the resulting graph is successively partitioned into two subgraphs in a hierarchical fashion, corresponding to the two most significant components of the actual image, until a termination condition is met. This graph-partitioning task is solved as a variant of the min-cut problem (normalized cut) using a hierarchical social (HS) metaheuristic. As a consequence of this iterative graph bipartition stage, pixels or regions are initially merged into the two most coherent components, which are successively bipartitioned.
according to this graph-splitting scheme. We applied the proposed approach to brightness segmentation on different standard test images, with good visual and objective segmentation quality results.

INTRODUCTION

Correct image segmentation is generally difficult to achieve and constitutes one of the most complex stages in image analysis. It usually represents a preliminary step for subsequent recognition and image understanding tasks. The segmentation problem consists of partitioning an image into its constituent semantically meaningful regions or objects (Gonzalez & Wood, 2002). The level of division depends on the specific problem being solved. This partition is accomplished in such a way that the pixels belonging to homogeneous regions with regard to one or more features (i.e., brightness, texture or colour) share the same label, and regions of pixels with significantly different features have different labels. Four objectives must usually be considered for developing an efficient generalized segmentation algorithm (Ho & Lee, 2003): continuous closed contours, non-oversegmentation, independence of threshold setting and short computation time. Specifically, the oversegmentation problem, which occurs when a single semantic object is divided into several regions, is a tendency of some segmentation methods, like watersheds (Haris, Efstatiadis, Maglaveras, & Katsaggelos, 1998; Hernández & Barner, 2000). Therefore, a subsequent region merging process is needed. In general, high-level knowledge of the input image would be useful in order to reduce the effect of incorrectly merged regions (Brox, 2001).

Many segmentation approaches have been proposed in the literature (Gonzalez & Wood, 2002; Parker, 1996; Sarkar et al., 2000; Sonka et al., 1999). The presented method can be considered as graph-based and pursues a high-level extraction of the image structures. Two kinds of graphs have been considered: pixel-based and region-based. The first approach represents the image as a weighted graph where nodes are the pixels in the original image and the edges together with their associated weights are defined using as local information the distance among pixels and their corresponding brightness values. The region-based graph approach requires an initial image oversegmentation (i.e., watershed transform) that produces a hierarchical top-down, region-based decomposition. To solve the segmentation problem, each pixel is assigned to a class or region by considering only local information (Gonzalez & Wood, 2002). This way, an image is represented by a simplified weighted undirected graph, called a modified region adjacency graph (MRAG). In the MRAG model, nodes are represented by the centres-of-gravity of each region resulting from the initial oversegmentation, and edges together with their associated weights are defined using the spatial distance between nodes, their corresponding brightness value and the corresponding region sizes. The MRAG structure is similar to the region adjacency graph (RAG) (Harris et al., 1998; Hernández & Barner, 2000; Sarkar et al., 2000) but MRAG also enables adding edges between pairs of nodes of non-adjacent regions.

Next, for both graph representations, a bipartition that minimizes the normalized cut value (Shi & Malik, 2000) for the image graph is computed. This process is successively repeated for each of the two resulting regions (image and subgraphs) using a binary splitting schema until a termination condition is met. The graph definition and the
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