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Eikonal-based region growing for efficient clustering ☆

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ABSTRACT

We describe an Eikonal-based algorithm for computing dense oversegmentation of an image, often called *superpixels*. This oversegmentation respects local image boundaries while limiting undersegmentation. The proposed algorithm relies on a region growing scheme, where the potential map used is not fixed and evolves during the diffusion. Refinement steps are also proposed to enhance at low cost the first oversegmentation. Quantitative comparisons on the Berkeley dataset show good performance on traditional metrics over current state-of-the art superpixel methods.

1. Introduction

With the increasing amount of available data, and the need for fast and accurate processing, the simplification of data becomes a crucial point for many applications. A convenient way to address this task is to consider that data can be modeled with a graph $G = (V, E, w)$, where V is the set of vertices, E is a set of edges, and $w > 0$ is the weight function that models the interaction between vertices. Exhibiting clusters of this graph leads to a simplification of the data and decreases the size of the problem. Many techniques of graph clustering have been proposed such as cut-based, spectral or random walk methods (see [16] for a comprehensive review of these techniques).

Recent works [3] adapt the eikonal equation to graphs in order to perform over-clustering from an initial set of annotated vertices V_0. Let $f : V \to \mathbb{R}$ be a real-valued function that assigns a real value $f(u)$ to each vertex $u \in V$. The reformulation of the Eikonal equation in the graph domain leads to the equation:

$$\begin{cases} \left\| \left(\nabla_w^f\right)(u) \right\|_p = P(u) & \forall u \in V \\ f(u) = \phi(u) & \forall u \in V_0 \end{cases} \quad (1)$$

where $(\nabla_w f)(u)$ is the weighted morphological gradient at a vertex u (see [11] for details), P is a positive function, and ϕ is an initialization function.

In this paper, we focus on grid graphs for image processing with the aim of grouping perceptually and adjacent pixels into meaningful regions, the so-called *superpixels*. Superpixels have become an important step in many computer vision applications such as segmentation [8,22], object localization [7], depth estimation [24], and scene labeling [5].

Some properties of an algorithm that generate superpixels are often desirable: (1) Superpixels should adhere well to object boundaries while limiting undersegmentation errors, (2) as superpixel methods are used as preprocessing, the algorithm should have a low complexity, and (3) it has to be simple to use (i.e. few parameters). In addition, some other properties may be desired: the control of the amount of superpixels, or the compactness of them.

Several superpixel algorithms exist in the literature, and they can be roughly divided into two approaches: The first consists in gradually growing superpixels from an initial set of centers. This approach includes Watershed [21], Turbopixels [10], SLIC [1], Consistent Segmentation [25] and Quick Shift [19]. The second approach relies on a graph formulation of the problem and aims at finding an optimal cut according to an objective function that takes similarities of neighboring pixels into account. This approach includes Entropy-based energy function method [12], optimal cuts [14,13], graph-cut [20], and agglomerative clustering of the nodes of the graph [6].

In this paper, we propose a new algorithm for superpixel generation: *Eikonal-based Region Growing Clustering*[1] (ERGC) that starts from an initial set of seeds and dilates them, and then refines the result oversegmentation by adding/moving cuts. It formulates the superpixel segmentation task as a solution of an Eikonal equation. Eq. (1) becomes:

$$\begin{cases} \|\nabla U(x)\| = F(x) & \forall x \in \mathcal{I} \\ U(x) = 0 & \forall x \in \Gamma \end{cases} \quad (2)$$

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[1] Source code and executable of ERGC can be found at https://sites.google.com/site/pierrebuyssens/ergc.

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0262-8856/

where $\mathcal{I}$ is the image domain, F a positive function, Γ the set of initial seeds, and $U(x)$ the traveling time or geodesic distance of x from source Γ. Focusing on grid graphs, it can be solved efficiently with the *Fast-Marching* method. The major change proposed in this paper concerns the function F, which is not fixed and evolves during the front evolution. It is detailed at Section 2.2.

ERGC is simple to use (by default, the only parameter is the desired number of superpixels), as fast as other superpixel methods, and outperforms them on two of the three traditional metrics.

The rest of the paper is organized as follows: Section 2 details the proposed potential function F, and the ERGC algorithm. Section 3 gives qualitative and quantitative comparisons of performances between ERGC and state-of-the-art methods. Some aspects and extensions of the proposed method are than discussed in Section 4, while Section 5 concludes the paper.

2. Superpixel method

2.1. Notations

In the following we adopt several notations to simplify the reading of the paper. A particular pixel of image $\mathcal{I}$ is noted $\boldsymbol{p}$ and consists of a coordinate couple $(x_{\boldsymbol{p}}, y_{\boldsymbol{p}})$. A region $\boldsymbol{R}_i$ consists of a seed pixel $\boldsymbol{s}_i$ and a size N_i in pixels. The color of a pixel $\boldsymbol{p}$ is noted $\boldsymbol{C}_{\boldsymbol{p}}$, and the mean color of a region R_i is noted $\boldsymbol{C}_{\boldsymbol{i}}$.

Note that the color images are considered in the CIELAB colorspace, so the color vector of a pixel (or a region) $\boldsymbol{C}$ reduces to $[l, a, b]^T$.

2.2. Proposed potential function

Since a superpixel method aims at grouping perceptually and adjacent pixels into meaningful regions, we propose a potential function F that conveys this desirable property. The right term of Eq. (2) is computed according to the mean color of the adjoining region:

$$F_c(\boldsymbol{p}, R_i) = \left\| \boldsymbol{C}_p - \boldsymbol{C}_i \right\|_2^2. \tag{3}$$

This potential function measures the perceptual color distance between the pixel $\boldsymbol{p}$ and the region R_i. For color images in the CIELAB colorspace, F reduces to:

$$F_c(\boldsymbol{p}, Ri) = \left(l_p - l_i\right)^2 + \left(a_p - a_i\right)^2 + \left(b_p - b_i\right)^2 \tag{4}$$

where $[l_i, a_i, b_i]^T$ is the mean color vector of region R_i.

In comparison to traditional gradient-based approaches [3] where $F(\boldsymbol{p}) = \|\nabla \mathcal{I}\|$, the proposed formulation favors the grouping of similar pixels, even for pixels that are far from the initial seeds (Fig. 2).

As a numerical solver of the Eikonal Eq. (2), we adopt the *Fast-Marching* method introduced by Sethian in [17]. It uses a priority queue to order the pixels as being the current estimate of the geodesic distance to the closest seed (see [15] for a detailed description of the *Fast-Marching* algorithm).

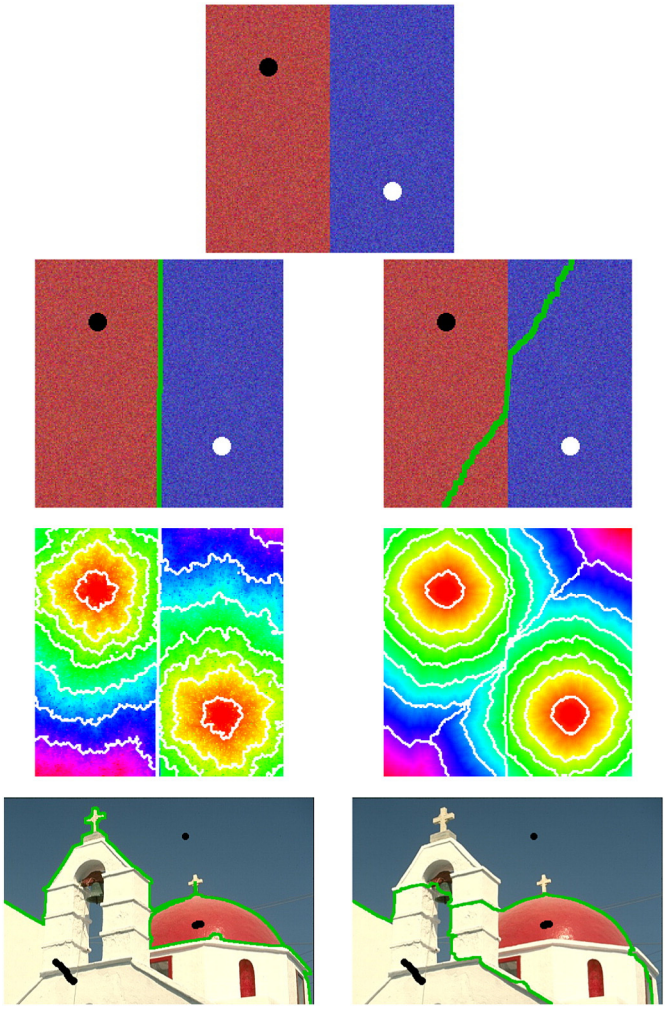

Fig. 2. First row: initial image. The back and white circles depict the initial seeds. Second row: the result segmentation with the proposed F (left) and the gradient-based potential function (right). Third row: geodesic distances map U in fake color. Some isocontours are shown in white. Last row: segmentation of a natural scene. Seeds are depicted in black. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Within the *Fast-Marching* algorithm, each time a pixel $\boldsymbol{p}$ is inserted to a region R_i, the attributes of this region are easily updated:

$$\begin{cases} \boldsymbol{C}_i & \leftarrow & \dfrac{\boldsymbol{C}_i \times N_i + \boldsymbol{C}_{\boldsymbol{p}}}{N_i + 1} \\ N_i & \leftarrow & N_i + 1 \end{cases}. \tag{5}$$

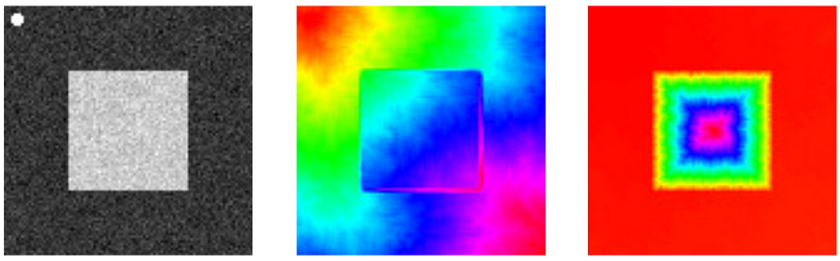

Fig. 1. Left: Initial image with the given seed depicted as the white dot. Middle: geodesic distance map U in false color obtained with the gradient-based potential function. Right: geodesic distance map obtained with the proposed potential function. A segmentation of the square based on the geodesic distances cannot be obtained with the gradient-based potential function. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)