SOCIETAL SEGMENTATION: A NOVEL SEGMENTATION METHOD

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ABSTRACT
A societal segmentation algorithm motivated by a region based parallel implementation is introduced. This algorithm is based on societal analogies related to the segmentation of a geographical area into villages and towns, and the corresponding behavioral rules. It actually includes certain principles of PDE, watershed and region-based segmentation methods while escaping most of their drawbacks.

1. INTRODUCTION

One of the most important tasks of an image analysis system is image segmentation, the identification of homogeneous regions in an image. Splitting an image into regions is part of its analysis. In this paper we introduce a novel segmentation algorithm based on societal considerations and following 2 main guidelines. First, we focus on real arbitrary images such as the ones observed by a robot in an unknown environment. That means we don’t consider segmentation methods dedicated to specific problems such as face recognition or using some image-dependant initialization such as using markers for initializing a watershed transform. The second guideline is a hardware one. Our applicative framework is that of low power vision chips relying on massively parallel computing resources [1][2] with dynamic reconfiguration and regional operators capabilities. Accordingly, our algorithm tries to make the most of the local and regional capabilities of these chips, but using only very simple and fast operators.

In the literature, several methods for segmentation have been proposed. We briefly review interesting features and drawbacks of 4 well-known and widely used segmentation methods, with our framework in mind.

1.1. Multi-resolution segmentation methods using predefined regions

Many algorithms use predetermined and fixed regions, whose size changes during the algorithm execution for multi-resolution purposes, but without adapting shape to actual image data [3]. In merge type algorithms, the size grows whereas in split type algorithms the size decreases. Because predetermined regions do not correspond to the actual images regions, such algorithms are obliged to go back and forth (iterated split and merge) and leave artifacts in the image anyway. For example, segmenting a ramp image (slowly going from white to black) with the CSC algorithm[3] leaves unwanted hexagonal patterns.

1.2. Active contours or surfaces methods

Active methods [4] [5] suppress the use of predetermined patterns for multi-resolution image analysis. They give excellent segmentation results in well-defined and specific cases. However, there are 2 main drawbacks when using them on arbitrary images. First, they need a good initialization, which is difficult to provide when nothing is known about the image. Secondly, these methods usually don’t provide a partition of an image with all of the objects segmented, but only with 1 or 2 objects that break away from the background. In our framework, using this class of algorithm is not really interesting because it doesn’t provides a partition of the image, and the functions used are usually complex and hard to implement in a massively parallel chip.

1.3. Partial differential equations (PDE) segmentation

Like snakes, PDE techniques [6] don’t use any predetermined pattern. They usually provide a high-quality partition of the image and they don’t have initialization problems. However their inherent limitation is that, computationally, each pixel only interacts with its immediate neighbors. Considerable acceleration could be obtained with regional type of interaction. Indeed, as shown in section 2.2, regional measures are useful for segmentation. Furthermore, vision chip may perform regional operations efficiently.

1.4. Watershed segmentation methods

The watershed transform [7] views its input as a topographic landscape in which valleys correspond to interior
pixels of regions, whereas mountain crests correspond to region edges. It is well suited to massively parallel implementation. One of its key features is its good accuracy in determining regions borders. However, it suffers from two major drawbacks: yielding over-segmented partitions and irregular borders when used with real images. This comes from the initialization step which considers every catchment basin from the initial gradient image as a region, including those created by the image noise in flat areas.

The first issue can be partly solved by merging over-segmented regions in a statistically reliable way. The method described in [8] merges regions by comparing their luminance arithmetical means depending on their size. However, we realize it doesn’t account enough for the border characteristics when merging 2 regions. The latter idea is implemented and detailed in our societal segmentation algorithm.

The problem of irregular region borders is a most important one. Necessarily some of the random irregular region shapes created at the initialization will be kept, especially on flat zones, and consequently, this second problem cannot be solved by a merging process only.

1.5. Heading for a new segmentation approach

Each of the presented methods have main strengths and drawbacks, however none of them is perfectly adapted to our framework. The one that best match our needs is the watershed transform. But even after some improvements [8], the problem of the irregular region borders and over-segmentation is still present. To cope with these issues, we need an algorithm with a more regular initialization and with advanced criteria to decide whenever it is relevant or not to merge regions.

In this paper we introduce a novel segmentation method based on a societal analogy: segmenting an image into regions is considered similar as segmenting a geographic area into villages and towns. This analogy highlights the fact that the mechanisms ruling the development of the local communities (such as villages or towns) in a country is an efficient segmentation method. We convert these societal rules into image segmentation rules to obtain a method we call societal segmentation.

Societal rules and segmentation algorithm are then detailed and justified using statistical arguments.

Finally, some segmented images are provided and commented in order to point out the key features of our algorithm.

2. INTRODUCING SOCIETAL SEGMENTATION

Segmentation is an important task in image processing, but it is also something happening naturally in real life. The watershed algorithm was inspired by the natural segmentation of rainfalls into different catchment basins. Similarly, in this paper, we present an analogy with a mixed geographical-societal segmentation process: the segmentation of a geographic area into villages and towns.

2.1. Analogies

What is a geographical area? It is a set of small pieces of land each having its own altitude.

What is a gray-scaled image? It is a set of pixels, each having its own luminance value.

What is a village? It is a subset of pieces of land having close geographical characteristics.

What is a region? It is a subset of adjacent pixels having close luminance characteristics.

Starting from these considerations, the analogy between image segmentation and country segmentation becomes clear if we consider that:

- An image is equivalent to a geographical area
- A region of an image is equivalent to a village
- A pixel is equivalent to a piece of land
- Altitude is equivalent to luminance

2.2. Principles

Based on the above equivalences, we now present the principles of a societal segmentation leading to a partition of a given area into villages.

To remove any a priori knowledge on the topography of the land, we assume there is one people in every piece of land at initialization.

The main question is how are villages formed? Village formation is the result of population growing, village-mergings and inter-village conflicts. These factors have multiple causes. Firstly, population growing is favored by the following factors:

- Possibility of local communication (local criterion): a locally flat land enhances population growing.
- Homogeneity and size of the village (global criterion): a big village should develop faster than a small one because communication between people is easier. However, if a village is not homogeneous (for example if its maximum altitude is very different for its minimum altitude), communication possibilities are reduced and the whole village develops at a lower pace.
- Possibility of communicating locally with the center of the village (mixed global-local criterion): if the local altitude of a piece of land is close to the average altitude of the village, communication with the economical center is improved and the increase of the population is favored.
- Diffusion of the population (local criterion): if a piece of land has much fewer inhabitants than those
in its close neighborhood (for example a border region after a conflict), it will attract some people coming from the adjacent pieces of land.

Secondly, region mergings can be interpreted as a vote held in each village during the merging phase of the algorithm. The goal of this vote is to decide whether there are neighboring villages (villages having a mutual border) with which it is suitable to merge. The arguments influencing the vote are the following ones:

- **Homogeneity of the 2 regions depending on their size (global criterion)**: as explained and justified in [8], two big regions must be very homogeneous to be merged (they must have almost the same average altitude) whereas two small regions can be merged even if they are not so homogeneous. This criterion, ensuring a statistically reliable segmentation is so important that the merging is canceled if it is not satisfied.

- **Size of the mutual border (mixed global-local criterion)**: as introduced in 1.4, it is meaningful to merge two big regions only if their mutual border is long enough compared to both of their surface square roots.

- **Height of the mutual border (mixed global-local criterion)**: In the same spirit, an important parameter for merging regions is the relative height of their mutual border. If this height is important, that means the 2 regions are separated by a mountain, and should not be merged even if they are globally homogeneous.

The two first evolution rules lead to a distribution of the population into regions. Thanks to the local, global, and mixed global-local criteria, there are interactions between each people, the whole population of a village, and its neighborhood. In each village, population is concentrated around the center, and the density is usually lower on the border line. Then, the reliability of the belonging of a piece of land to a village can be estimated by the number of people living there. This property also allows to quantify the reliability of a border line.

However, border reliability presents a paradox. Due to the first growing rule (a locally flat land enhances population growing), border population and consequently reliability is higher in flat than in mountainous areas. Yet, the border is easier to define in mountainous area with large altitude gradients than in flat areas having rather arbitrary borders (typically noisy borders in the case of the watershed segmentation algorithm).

This paradox is solved considering a third evolution rule: the inter-village conflicts. In flat regions, uncertain border leads to local conflicts for the control of the zone. During these conflicts, people are killed and the populations on both sides of the frontier decrease, thus reducing the reliability of the border. Consequently, the paradox is removed.

**2.3. Formalization**

Transposition to image segmentation of the geographical segmentation by societal rules is simple using the analogies already presented. The rules presented in a literary way are now mathematically described. Let $p$ be the population in each pixel, $x$ the luminance and $A$ is the area of a region. Border values are noted $x_b$. $K_n$ and $a_n$ are constants.

**Population growing rules** additively combine the following equations: (1a) shows the effects of local communication, (1b) shows the influence of homogeneity and size of the region, (1c) shows the consequences of local to regional communication, and (1d) describes the population diffusion.

\[
\frac{\partial p}{\partial t} = \frac{1}{|\nabla p| + a_1} \tag{1a}
\]

\[
\frac{\partial p}{\partial t} = \frac{1}{(\max_{reg}(x) - \min_{reg}(x)) + a_2} \tag{1b}
\]

\[
\frac{\partial p}{\partial t} = \frac{1}{|x - \bar{x}| + a_3} \tag{1c}
\]

\[
\frac{\partial p}{\partial t} = \Delta p \tag{1d}
\]

**Region merging rules** result from a voting process. Each parameter has one vote (2a, 2b, 2c) and the region to merge is the one having the best score. The merging is done if only

![Fig. 1. Segmentation example of a medical image.](image-url)
the top score is greater than 2 (2d).

\[
\begin{align*}
\text{if } (x_2 - x_1) \sqrt{\max(S_1, S_2)} < K_1 \text{ then } V_1 &= 1 \quad (2a) \\
\text{if } \frac{\text{len}(x_b)}{S_1} > K_2 \text{ or } \frac{\text{len}(x_b)}{S_2} > K_2 \text{ then } V_2 &= 1 \quad (2b) \\
\text{if } \max((x_2 - x_1), (x_2 - x_2)) < K_3 \text{ then } V_3 &= 1 \quad (2c) \\
\text{if } V_1 + V_2 + V_3 > 2 \text{ then merging is ok.} \quad (2d)
\end{align*}
\]

**Inter-regional conflicts**: equation (3) shows the effects of the flatness of the border on the population each time a inter-regional conflicts happens.

\[
\frac{d p_b}{dt} = -K \frac{1}{|\nabla p| + a_4 p_b} \quad (3)
\]

### 2.4. Algorithm

The algorithm is initialized with a population of 1 in each pixel. Such an initialization, compared to watershed initialization, reduces the border irregularities of the final segmentation. Constants \(K_n\) are set-up only depending on the size and the contrast of the initial image whereas constants \(a_n\) just avoid a division by zero (and can be set to 1). Then, population growing, region merging and inter-regional conflicts are performed iteratively until the stabilization of the algorithm. The latter is guaranteed thanks to the k-idempotence of the merging process.

### 2.5. Results

First results of our algorithm (presented in Fig.1 and Fig.2) match high quality standard ones. It produces a segmentation where small significant regions and where large homogeneous regions are well segmented. Additionally, it gives indications on the reliability of a border (border are represented by a red line, and the reliability is represented by the red density). Furthermore, the obtained borders are smoother than those produced by the watershed algorithm.

Convergence of our algorithm is fast : its temporal complexity is \(O(\log_2(A))\), where A is the area of the whole image, provided that regional operators are available (as in our vision chip). This is a major advantage compared with PDE methods (since they are only local), while matching their quality.

We have tested the algorithm on a wide set of images and robustness seems to be one of its key features (important changes on constants have little effect on the result).

A comparison with other algorithms and extensive results on the robustness of our *societal segmentation* algorithm will be provided later.

### 3. CONCLUSION

Subject to particular constraints of parallel implementation and in order to process arbitrary images, a novel segmentation algorithm we call *societal segmentation* has been proposed. This method, transposed from geographical segmentation by societal rules, is related to partial differential equations by some of its population growing rules, and also to region-based and watershed algorithms.

It produces a high quality standard segmentation with interesting properties such as returning a statistically reliable segmentation, segmenting fuzzy areas or reducing the irregularities of region borders. Furthermore, it gives information whether the segmentation is locally reliable or not.

### 4. REFERENCES