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# A Marker Controlled Watershed Algorithm

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**Abstract:** This paper is an attempt to develop an image segmentation algorithm using the marker controlled watershed algorithm. The initial low-level segmentation step is considered as the major need for the fine segmentation. This low level segmentation must be of lower computational complexity and of lower time consuming. The watershed is the movement of the water from the catchment area to the place where water sources meet. The watershed in the image is similar to the catchment basin of a height map. The watershed lines are the defined on edges, nodes and also in the hybrid lines which lie on both nodes and edges. A spatially regularized gradient is introduced in order to a tunabletrade-off between the regularity and the adherence to the object boundaries. Matlab based implementation is carried out and the results are tabulated and the results are compared with the previous implementation.

**Keywords:** Super pixels, watershed, segmentation.

## I. INTRODUCTION

The superpixels are obtained as a result of the initial segmentation step which is the initial step for the further steps like the segmentation and classification. The computational complexity of the rest of the steps in the further algorithms is reduced due to the proper use of this initial segmentation steps. The superpixels should have the following properties in order to have an efficient overall computational complexity.

1. Homogeneity: The pixels in the super pixels must have the similar or the related pixel values.
2. Connected Partition: This superpixel must comprise the part of the image, which would be a single connected component.
3. Adherence to object boundaries: The super pixels boundary must be same as the object boundary at the edges.
4. Regularity: The super pixels must form a pattern that look regular on the image. This property is often desirable as it makes the SP more convenient to use for subsequent analysis steps.

The requirements on regularity and boundary adherence are to a certain extent oppositional and a good solution typically aims at finding a compromise between these two requirements.We therefore hypothesized that the Watershed transformation [1], [2] should be an interesting candidate for superpixelgeneration, as it has been shown to achieve state-of-the-art performance in many segmentation problems, it is non-parametric, and there exist linear-complexity algorithms to compute it, as well as efficient implementations [3], [4].

(a)

(b)

Figure 1 Superpixels illustration. The original image comes from the Berkeleysegmentation database. (a) Original image. (b) Waterpixels.

The only often cited drawback, oversegmentation, does not seem to be problematic for superpixel generation, as long as we can control the degree of oversegmentation (number of superpixels), and the regularity of the resulting partition. Given these considerations, we propose a strategy for applying the watershed transform to superpixel generation, where we use a spatially regularized gradient to achieve a tunable trade-off between superpixel regularity and adherence to object boundaries. We quantitatively evaluate our method on the Berkeley segmentation database and show that we outperform the best linear-time state-of-the art method: Simple Linear Iterative Clustering (SLIC) [5]. We call the resulting superpixels “waterpixels.”

## II. RELATED WORK

In addition to these requirements on superpixel quality, computational efficiency is an absolutely essential aspect, as the partition into superpixels is typically only the first step of an often complex and potentially time consuming workflow. Methods of linear complexity are consequently of particular interest.
We therefore hypothesized that the Watershed transforma- tion [1], [2] should be an interesting candidate for superpixel generation, as it has been shown to achieve state-of-the-art performance in many segmentation problems, it is non-parametric, and there exist linear-complexity algorithms to compute it, as well as efficient implementations [3], [4]. The only often cited drawback, oversegmentation, does not seem to be problematic for superpixel generation, as long as we can control the degree of oversegmentation (number of superpixels), and the regularity of the resulting partition.

Given these considerations, we propose a strategy for applying the watershed transform to superpixel generation, where we use a spatially regularized gradient to achieve a tunable trade-off between superpixel regularity and adherence to object boundaries. We quantitatively evaluate our method on the Berkeley segmentation database and show that we outperform the best linear-time state-of-the art method: Simple Linear Iterative Clustering (SLIC) [5]. We call the resulting superpixels “waterpixels.” Low-level segmentations have been used for a long time as first step towards segmentation [7], [8]. The term superpixel was coined much later [9], albeit in a more constrained frame- work. This approach has raised increasing interest since then. Various methods exist to compute SPs, most of them based on graphs [10], geometrical flows [11] or k-means [5]. We will focus on linear complexity methods generating regular SPs. Even though methods inspired by general clustering meth- ods (type 2) seem appealing at first sight, in particular when they globally optimize a cost function, this class of methods does not guarantee connectivity of the superpixels for arbi- trary choices of the pixel-seed distance (see [5], [12]). For instance, the distance metric proposed in [5] (a combination of Euclidean and grey level distance), leads to non-connected superpixels, which is undesirable. To solve this issue, a post- processing step is necessary, consisting either in relabeling the image so that every connected component has its own label (see [12]), leading to a more irregular distribution of SP sizes and shapes, or in reassigning isolated regions to the closest and large enough Superpixel, as in [5], leading to non-optimality of the solution and an unpredictable number of superpixels. In addition, such postprocessing increases the computational cost and can turn out to be the most time-consuming step when the image contains numerous small objects/details compared to the size of the Superpixel. It is generally accepted that a good superpixel-generation method should provide to the user total control over the num- ber of resulting Superpixels. While this property is achieved by [11]–[14], some only reach approximatively this num- ber because of post-processing (either by splitting too big superpixels, or removing small

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isolated superpixels as in [5]). Another parameter is the control on superpixels regularity in the trade-off between regularity and adherence to contours. As far as performance is concerned, one of the main criteria is undoubtedly the complexity that the method requires. Indeed, for Superpixels to be used as primitives for further analysis such as classification, their computation should neither take too long nor too much memory. This is the reason why we focus on linear complexity methods. Among them, SLIC appears to offer the best performance with regards to the trade-off between adherence to boundaries and regularity [5]. Moreover, since its recent inception, this method has become very popular in the computer vision community.

**Problem Statement:**
The requirements on regularity and boundary adherence are to a certain extent oppositional, and a good solution typically aims at finding a compromise between these two requirements.
In addition to these requirements on superpixel quality, computational efficiency is an absolutely essential aspect, as the partition into superpixels is typically only the first step of an often complex and potentially time consuming workflow. Methods of linear complexity are consequently of particular interest.

## III. WATERSHED BASED IMAGE SEGMENTATION

Watershed transformation also called, as watershed method is a powerful mathematical morphological tool for the image segmentation. It is more popular in the fields like biomedical and medical image processing, and computer vision [4]. In geography,watershed means the ridge that divides areas drained by different river systems. If image is viewed as geological landscape, the watershed lines determineboundaries which separate image regions. The watershed transform computes catchment basins and ridgelines (also known as watershed lines), where catchment basins corresponding to image regions and ridgelines relating to region boundaries [5]. Segmentation by watershed embodies many of the concepts of the three techniques such as threshold based, edge based and region based segmentation. Watershed algorithms based on watershed transformation have mainly two classes. The firstclass contains the flooding based watershed algorithms and it is a traditional approach whereas the second class contains rain falling based watershed algorithms. Many algorithms have been proposed in both classes but connected components basedwatershed algorithm [2] shows very good performance compared to all others. It comes under the rain falling based watershed algorithm approach. It gives very good segmentation results, and meets the criteria of less computational complexity for hardware implementation. Generation of superpixels is shown in the figure below.

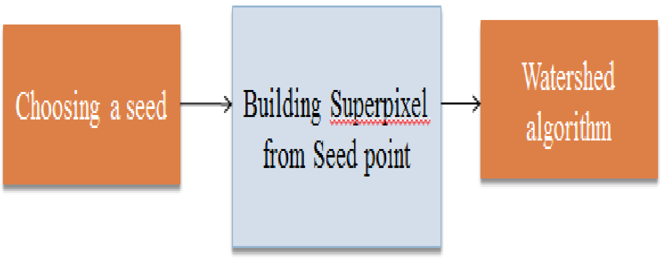


Figure 2: Generation of SP

As most watershed-based segmentation methods, waterpixels are based on two steps: the definition of markers, from which the flooding starts, and the definition of a gradient (the image to be flooded). We propose to design these steps in such a way that regularity is encouraged.

A waterpixel-generation method is characterized by the following steps:

1) Computation of the gradient of the image;
2) Definition of regular cells on the image, centered on the vertices of a regular grid;
3) Selection of one marker per cell;
4) Spatial regularization of the gradient with the help of a distance function;
5) Application of the watershed transformation on the regularized gradient defined in step 4 from the markers defined in step 2.

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### A. Choosing the Seeds

In the first step, a set of seeds is chosen, which are typically spaced regularly over the image plane and which can be either regions or single pixels:

•Type A seeds are independent of the image content. These are typically the cells or the centers of a regular grid.

•Type B seeds depend on the content of the image (compromise between a regular cover of the image plane and an adaption to the contour).

•Type C seeds are initially image independent, then they are iteratively refined to take into account the image contents. If the seed does not depend on the image, an iterative refinement is usually preferable, and therefore more time is spent on the computation of the SP. Type B methods may spend more time on finding appropriate seeds, but can therefore afford not to iterate the SP generation.

### B. Building SuperpixelsFrom Seeds

In the second step, the partition into superpixels is built from the seeds. Among the methods with linear complexity, there are two main strategies for this: Shortest Path Methods (Type 1) [11], [13]:these methods are based on region growing: they start from a set of seeds (points or regions) and successively extend them by incorporating pixels in their neighborhood according to a usually image dependent cost function until every pixel of the image plane has been assigned to exactly one superpixel. This process may or may not be iterated. Shortest Distance Methods (Type 2) [5], [12]:these are iterative procedures inspired by the field of unsupervised learning, where at each iteration step, seeds (such as centroids) are calculated from the previous partition and pixels are then re-assigned to the closest seed (like for example the k-means approach). Even though methods inspired by general clustering methods (type 2) seem appealing at first sight, in particular when they globally optimize a cost function, this class of methods does not guarantee connectivity of the superpixels for arbitrary choices of the pixel-seed distance (see [5], [12]). For instance, the distance metric proposed in [5] (a combination of Euclidean and grey level distance), leads to non-connected superpixels, which is undesirable. To solve this issue, a postprocessing step is necessary, consisting either in relabeling the image so that every connected component has its own label (see [12]), leading to a more irregular distribution of SP sizes and shapes, or in reassigning isolated regions to the closest and large enough Superpixel, as in [5], leading to non-optimality of the solution and an unpredictable number of superpixels.

In addition, such postprocessing increases the computational cost and can turn out to be the most time-consuming step when the image contains numerous small objects/details compared to the size of the Superpixel. On the contrary, methods based on region growing (type 1) inherently implement a “path-type” distance, where the distance between two pixels does not only depend on value and position of the pixels themselves, but on values and positions along the path connecting them. Type 1 methods imply connected superpixel regions, for which the number of superpixels is exactly the number of seeds.

### C. Other Properties

It is generally accepted that a good superpixel-generation method should provide to the user total control over the number of resulting Superpixels. While this property is achieved by [11]–[14], some only reach approximatively this number because of post-processing (either by splitting too big superpixels, or removing small isolated superpixels as in [5]). Another parameter is the control on superpixels regularity in the trade-off between regularity and adherence to contours. Only [5] and [12] enable the user to weight the importance

## IV. WATERPIXELS

Author As most watershed-based segmentation methods, waterpixels are based on two steps: the definition of markers, from which the flooding starts, and the definition of a gradient (the image to be flooded). We propose to design these steps in such a way that regularity is encouraged. The formation of waterpixels is shown in the figure 3. A waterpixel-generation method is characterized by the following steps:

1) Computation of the gradient of the image;
2) Definition of regular cells on the image, centered on the vertices of a regular grid;
3) Selection of one marker per cell;
4) Spatial regularization of the gradient with the help of a distance function;
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These steps are illustrated in figure 3 and developed in the next paragraphs.

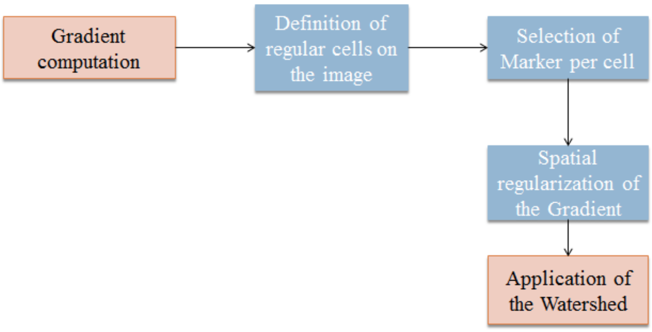


Figure 3: Formation of waterpixels

**A. Gradient and Cells Definition**
Let f :D → V be an image, where D is a rectangular subset of Z2, and V a set of values, typically {0, . . . , 255}when f is a grey level image, or {0, . . . , 255}3 for color images.
The first step consists in computing the gradient image g of the image f . The choice of the gradient operator dependson the image type, e.g. for grey level images we mightchoose a morphological gradient. This gradient will be usedto choose the seeds (section III-B) and to build the regularizedgradient (III-C).For the definition of cells, we first choose a set of N points{oi}1≤i≤N in D, called cell centers, so that they are placed onthe vertices of a regular grid (a square or hexagonal one forexample). Given a distance d on D, we denote by σ the gridstep, i.e. the distance between closest grid points.A Voronoitesselation allows to associate to each oiaVoronoicell . For each such cell, a homothety centered on oiwith factor ρ (0 < ρ ≤ 1) leads to the computation of thefinal cell Ci. This last step allows for the creation of a marginbetween neighbouring cells, in order to avoid the selection ofmarkers too close from each other.

**B. Selection of the Markers**
As each cell is meant to correspond to the generation of a unique waterpixel, our method, through the choice of one marker per cell, offers total control over the number of SP, with a strong impact on their size and shape if desired. First, we compute the minima of the gradient g. Each minimum is a connected component, composed of one or more pixels. These minima are truncated along the grid, i.e. pixels which fall on the margins between cells are removed. Second, every cell of the grid serves to define a region of interest in the gradient image. The content of g in this very region is then analyzed to select a unique marker, as explained in the next paragraph.
For each cell, the corresponding marker is chosen among the minima of g which are present in this very cell. If several minima are present, then the one with the highest surface extinction value [19] is used. We have found surface extinction values to give the best performances compared with volume and dynamic extinction values (data not shown). It may happen that there is no minimum in a cell. This is an uncommon situation in natural images.
In such cases, we must add a marker for the cell which is not a minimum of g, in order to keep regularity. One solution could be to simply choose the center of the cell; however, if this point falls on a local maximum of the gradient g, the resulting SP may coincide with the maximum region and therefore be small in size (leading to a larger variability in size of the SP). We propose instead to take, as marker, the flat zone with minimum value of the gradient inside this very cell. In both cases (i.e. either there exists at least one minimum in the cell or there is not), the selected marker has to be composed of a unique connected component to ensure regularity and connectivity of the resulting superpixel. However, it might not be the case, respectively if more than one minimumhave the same highest extinction value, or if more than one flat zone present the same lowest gradient value in the cell. Therefore, an additional step enables to keep only one of the connected components if there is more than one potential “best” candidate.
The set of resulting markers is denoted {Mi}1≥i≥N,Mi⊂D. The result of the marker selection procedure is illustrated in Figure 4 c.

**C. Spatial Regularization of the Gradient and Watershed**
The selection of markers has enforced the pertinence of future superpixel-boundaries but also the regularity of their pattern (by imposing only one marker per cell). In this paragraph, we design a spatially regularized gradient in order to

further compromise between boundary adherence and regularity. Let Q = {qi }1≤i≤N be a set of N connected components of the image f. For all p ∈D, we can define a distance function dQwith respect to Q as follows: ∀p ∈D, dQ(p) = 2σ mini∈[1,N] d(p, qi ) (1) where σ is the grid step defined in the previous section.

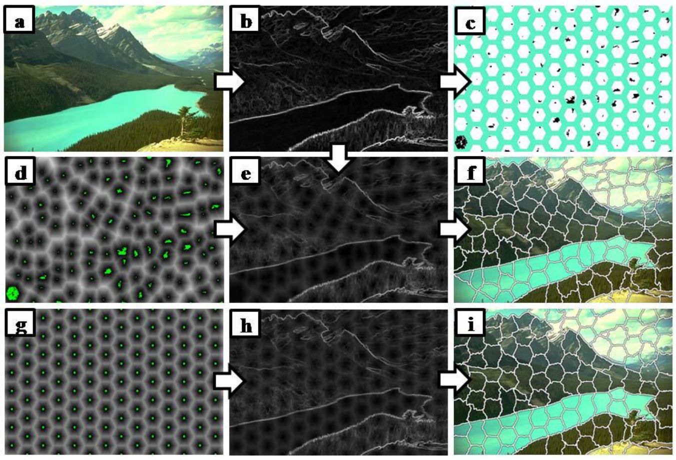


Figure 4: Illustration of waterpixels generation: (a): original image; (b) corresponding Lab gradient; (c): selected markers within the regular grid of hexagonal cells (step σ = 40 pixels); (d): distance function to markers; (g): distance function to cell centers; (e) and (h): spatially regularized gradient respectively with distance functions to selected markers (d) and to cell centers (g); (f) and (i): Resulting waterpixels obtained by respectively applying the watershed transformation to (e) and (h), with markers (c).

The normalization by σ is introduced to make the regularization independent from the chosen SP size. We have studied two possible choices of the qi . The first one is to choose them equal to the markers: qi = Mi. Resulting waterpixels are called m-waterpixels. The second one consists in setting them at the cell centers: qi = oi, which leads to c-waterpixels. We have found that the first gives the best adherence to object boundaries, while the second produces more regular superpixels. The spatially regularized gradient gregis defined as follows: greg= g + kdQ(2) where g is the gradient of the image f , dQis the distance function defined above and k is the spatial regularization parameter, which takes its values within _+. The choice of k is application dependent: when k equals zero, no regularization of the gradient is applied; when k → ∞, we approach the Voronoi tessellation of the set {qi }1≥i≥N in the spatial domain. In the final step, we apply the watershed transformation on the spatially regularized gradient greg, starting the flooding from the markers {Mi}1≤i≤N , so that an image partition {si}1≤i≤N is obtained. The siare the resulting waterpixels.

## CONCLUSION

This paper introduces waterpixels, a family of methods for computing regular superpixels based on the watershed transformation. Both adherences to object boundaries and regularity of resulting regions are encouraged thanks to the choice of the markers and the gradient to be flooded. Different design options, such as the distance function used to spatially regularized the gradient, lead to different trade-offs between both properties. The computational complexity of waterpixels is linear. Our current implementation makes it one of the fastest superpixel methods. Experimental results show that waterpixels are competitive with respect to the state-of-the art. They outperform SLIC superpixels, both in terms of quality and speed. The trade-off between speed and segmentation quality achieved by waterpixels, as well as their ability to generate hierarchical segmentations at negligible extra cost, offer interesting perspectives for this superpixels generation method.

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