WATERSHED, HIERARCHICAL SEGMENTATION AND WATERFALL ALGORITHM

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Abstract

A major drawback when using the watershed transformation as a segmentation tool comes from the over-segmentation of the image. Over-segmentation is produced by the great number of minima embedded in the image or in its gradient. A powerful technique has been designed to suppress over-segmentation by a primary selection of markers pointing out the regions or objects to be segmented in the image. However, this approach can be used only if we are able to compute the marker set before applying the watershed transformation. But, in many cases and especially for complex scenes, this is not possible and an alternative technique must be used to reduce the over-segmentation. This technique is based on mosaic images and on the computation of a watershed transform on a valued graph derived from the mosaic images. This approach leads to a hierarchical segmentation of the image and considerably reduces over-segmentation.

Then, this hierarchical segmentation is redefined by means of a new algorithm called the waterfall algorithm. This algorithm allows the selection of minima and of catchment basins of higher significance compared to their neighborhood. A very powerful implementation of this algorithm using geodesic reconstruction of functions is also presented.

Finally, this approach is compared to another powerful tool introduced by M. Grimaud for selecting significant extrema in an image: the dynamics.

Keywords: image analysis, mathematical morphology, watershed, hierarchical segmentation, waterfall algorithm, image reconstruction

1. Introduction

Image segmentation based on the use of the watershed transformation has proved to be an efficient method provided that the main drawback of this technique is suppressed. This drawback consists in the over-segmentation produced by the watershed transformation if applied directly on the images to be segmented. A solution for preventing this over-segmentation is well known and has been widely used in various examples [1, 2]. It consists in a prior selection of the objects or regions to be extracted in the image. This selection gives a collection of markers which are introduced in the watershed algorithm allowing the segmentation of the selected regions exclusively. Unfortunately, because of the complexity of the regions in a real scene, this marking is often difficult and sometimes even impossible. It is not always simple to associate obvious geometric or photometric characteristics with the objects to be segmented.

This paper deals with another approach for eliminating the over-segmentation problem. This approach is based on a hierarchical segmentation of the image aiming at merging the catchment basins of the watershed image belonging to almost homogeneous regions. This technique leads to various algorithms. The most efficient however, still uses the watershed transformation and the image reconstruction. Both tools are already used in the traditional process of segmentation in mathematical morphology.

The hierarchical segmentation will be described first (Sec. 2). It uses a simplified image called mosaic image. Then another algorithm, called the waterfall algorithm, will be presented (Sec. 3). The relationship between this algorithm and the hierarchical segmentation will also be emphasized. Finally, a comparison between these techniques and another transformation called dynamics will be made (Sec. 4).

2. The hierarchical segmentation

The best introduction of the hierarchical segmentation can be made by means of an image simplification process producing, from the original image f, a new image called the mosaic image or partition image [1].

2.1 Mosaic image: definition and building

Let f be a grey tone image and g be its morphological gradient. Let $W(g)$ be the watershed transformation of g. This watershed produces many catchment basins. Each catchment basin CB_i is associated with a minimum m_i of the gradient g. Let us calculate the average value f_i of the function f in the minimum m_i. In fact, in many cases, the minimum m_i corresponds to a zero-valued gradient and therefore f is constant and equal to f_i in m_i. A new function f' can then be defined by extending the value f_i to the entire catchment basin CB_i. This new function is called the mosaic image of f.

In practice, the watershed line C_{ij} separating two adjacent catchment basins CB_i and CB_j is given either the value f_i or the value f_j. This enables the definition of the mosaic image on the whole space and has no consequence on the following use of this simplified image. We notice that the watershed of this new image f is equal to the watershed of the initial image f.

2.2 Gradient of the mosaic image

Let us consider again two adjacent catchment basins CB_i and CB_j with respective values f_i and f_j. We define the gradient of the mosaic image h on every arc C_{ij} separating CB_i and CB_j by $h\left(C_{ij}\right) = |f_j - f_i|$.

2.3 Hierarchy and suppression of the over-segmentation

Starting from the mosaic image f' and from its gradient h, let us introduce a hierarchical process able to suppress the over-segmentation.

When we look at a picture, the distinction between more or less homogeneous regions is quite obvious despite the fact that these regions may be over-segmented by the watershed transformation. This over-segmentation is produced by low contrast variations inside these homogeneous regions. If we consider the arcs of the watershed inside the homogeneous regions, the value of the gradient of the mosaic image is lower than the values corresponding to the arcs separating different homogeneous regions. A solution for eliminating these arcs would consist in thresholding the watershed lines. However this solution is difficult to implement, because, on the one hand, a suitable threshold value must be chosen and on the other hand, it is not sure that such a value exists. This is why the criterion used in the hierarchy is not a threshold but simply the fact that the gradient values are lower on the inside arcs than on the surrounding arcs. Consider Fig. 1a, representing the gradient of the mosaic image of a very simple homogeneous region split by a unique inside arc. The gradient value of this inside arc is lower than the gradient values of the arcs which contour the homogeneous region. If the over-segmentation of the homogeneous region was more severe, the resulting aspect of the gradient image would be the same: no inside arc greater than the surrounding ones or at least, no closed curve made of inside arcs all of them greater than the surrounding ones.

Let us define then a graph on the gradient of the mosaic image. Each arc C_{ij} of the watershed lines corresponds to a vertex of the graph. Then each vertex of this graph is the neighbor of another vertex if the arcs corresponding to these vertices surround the same catchment basin of the watershed (Fig. 1b). This graph is not a planar graph. However, each vertex can be valued with the gradient of the mosaic image (on each arc, it is a constant). The watershed transformation can be performed on this valued graph. The flooding starts from the arcs with a minimum valuation (the inside arcs, Fig. 1c) and propagates towards the other arcs. Finally, the watershed lines are made of those arcs which surround the homogeneous regions. This transformation produces exactly the desired result. The new catchment basins are made of all the inside arcs which are connected in the graph defined above. These arcs can be removed and the catchment basins of the primary watershed separated by these arcs can be

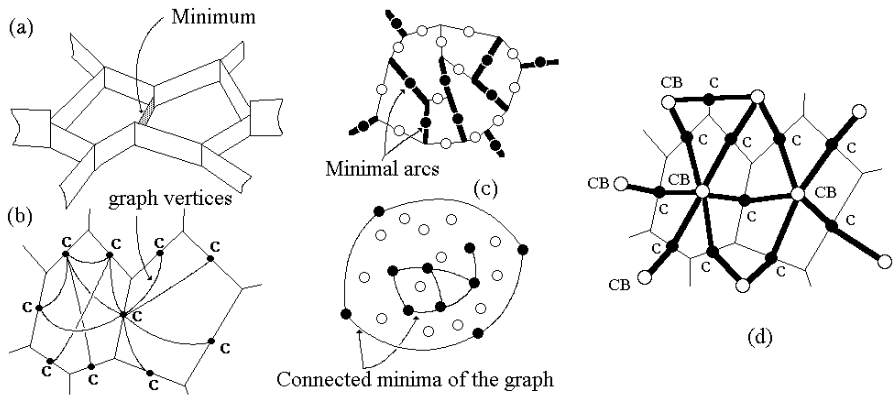

Figure 1. a) 3D representation of the gradient of a simple mosaic b) associated graph c) minimal arcs and their correspondence on the graph d) planar 6 representation of the above graph.

merged. The result is a new segmented image where the over-segmentation of the homogeneous regions has been suppressed.

2.4 Hierarchical algorithms

The preceding graph is not easy to handle because it is not a planar graph. Although the watershed transformation can be extended in a straightforward way to 3D structures, in this particular case, it is possible to transform this non planar graph into a planar one by adding vertices corresponding to the primary catchment basins (Fig. 1d). These new vertices provide an intermediary connection between the neighboring vertices of the non planar graph. These vertices, however must be valued. Their valuation $v(CB_i)$ is given by $v\left(CB_i\right) = \inf_j\left(h\left(C_{ij}\right)\right)$. This valuation corresponds to the value of the lowest arc contouring the basin CB_i. Finally, this new representation leads to a third one which has the form of an image h', given by $h'\left(x\right) = h\left(C_{ij}\right)$ iff $x \in C_{ij}$ and $h'\left(x\right) = v\left(CB_i\right)$ iff $x \in CB_i$.

This image h' is called the hierarchical image. The hierarchical process can then be performed on this image, in a very simple way, by performing the watershed transformation of h'. The only precaution consists here in replacing the watershed lines which do not belong to the initial watershed transform of g (they are inside an initial catchment basin) by the watershed lines which contour this catchment basin.

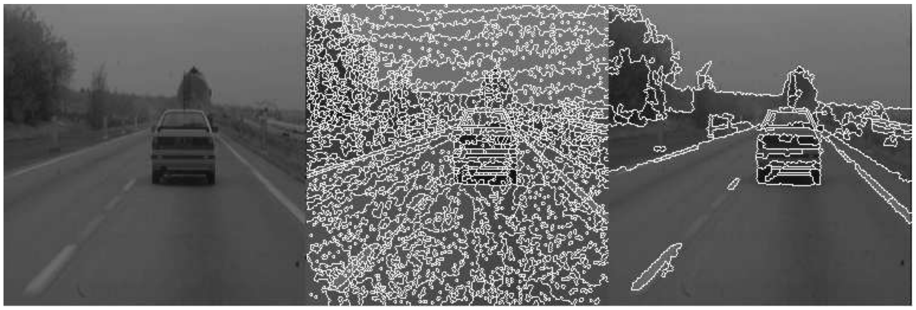

Figure 2. a) initial road scene b) over-segmented watershed of the gradient image c) hierarchical segmentation, most of the over-segmentation has been removed.

2.5 Example

Figs. 2a to 2c illustrate the efficiency of the hierarchical segmentation for reducing the over-segmentation. In this example, the road is a rather homogeneous object, but it appears nonetheless to be over-segmented (Fig. 2b). After the hierarchical processing depicted above, this over-segmentation has been removed and the road corresponds to a unique catchment basin which can be considered as the road marker in further processings.

3. Waterfall algorithm

Let us describe another hierarchical algorithm. This algorithm does not use the mosaic image but directly the initial function f.

3.1 The waterfall algorithm principle

Consider a function f as illustrated at Fig. 3.

Although the function used in this example is one dimensional, the notion introduced in the following is general and can be applied to any function. Among the various minima of the function f, three of them m_1 , m_2 and m_3 are interesting because they mark regions of higher importance in the image. If f is a gradient image for instance, m_1 could be the marker of an object to be segmented and m_2 and m_3 could be the outside markers. The other minima could be produced by noise. The watershed transformation of f produces as many catchment basins as there are minima (Fig. 3a). On the contrary, if only m_1, m_2 and m_3 are used by the watershed transform, only three catchment basins will appear (Fig. 3b). Two questions then arise. The first one is to characterize the minima m_1, m_2 and m_3. The second one is to find a way to determine automatically the catchment basin associated with the minimum m_1 for instance, without any a priori knowledge or construction of the primary wa-

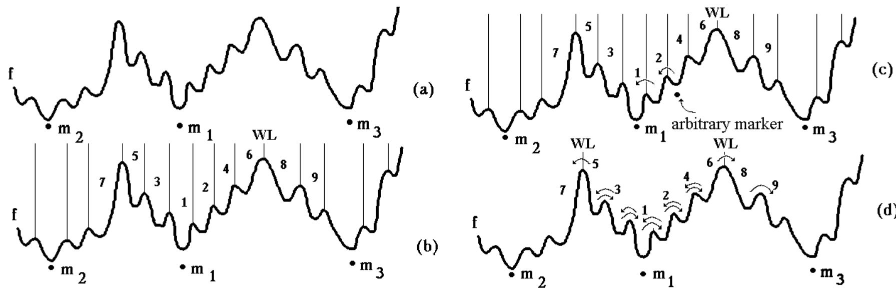

Figure 3. a) primary watershed of the function f b) significant minima and the corresponding watersheds c) selection of a minimum and waterfalls towards the significant marker d) symmetrical waterfalls between adjacent catchment basins.

tershed transformation. These two questions are answered through the notion of waterfall [1].

Significant markers characterization. One could think that the significant minima correspond to locally deepest minima of the function f. However, consider (Fig. 3c) a given minimum m. If we flood the catchment basin associated with this minimum, an overflow occurs when the lowest saddle point separating this catchment basin from an adjacent catchment basin is reached. This new catchment basin, then, is flooded and overflows either towards the preceding catchment basin or towards a new one. In the former case, the first minimum is a significant minimum. In the latter case, the first minimum is not significant. More generally, a minimum is said to be significant if the waterfall coming from its corresponding catchment basin pours in an adjacent catchment basin which, in turn, when flooded, overflows towards the first minimum. In fact, and for obvious reasons of symmetry, a significant minimum is not unique, and the minima linked by symmetrical waterfalls are equally significant. Moreover, it is equivalent to consider as a significant marker the arc of the primary watershed line separating the catchment basins linked by symmetrical overflows. This significant marker is an arc of minimum height of the primary watershed.

Determining the catchment basin corresponding to a significant marker set. A similar procedure based on waterfalls can be used to determine the entire catchment basin corresponding to a significant marker, made of primary catchment basins linked by symmetrical waterfalls. Consider the function f and a marker set made of at least two catchment basins CB_1 and CB_2 (see Fig. 3d). The arc C_{12} separating these catchment basins can be equivalently considered as the significant marker. Let us flood these two catchment basins.

The water will pour into the basin CB_3. But if we flood CB_3, the water will pour into $CB_1 \cap CB_2$. So, because of the appearance of symmetric waterfalls over the arc C_{13}, this arc is removed and the three basins are merged. Let us continue our flooding process. The water coming from $CB_1 \cup CB_2 \cup CB_3$ will pour into CB_5. Finally all the catchment basins CB_1 to CB_6 will be merged because the waterfalls from a given basin to another one are symmetrical versus the arcs which separate them. On the contrary, the watershed line between CB_6 and CB_8 will not be removed because, if $CB_1 \cup \ldots \cup CB_6$ pours into CB_8, CB_8 pours into CB_9 first. At the end, the remaining watershed lines contour the catchment basin associated with the significant marker.

3.2 An efficient algorithm based on reconstruction

The main drawback of the previous algorithm comes from the fact that the waterfalls must be checked individually for every minimum or catchment basin of the primary watershed. This leads to a very slow and boring process. Fortunately, there exists a faster procedure based on image reconstruction.

Image reconstruction. Consider two functions f and g, with $f \geq g$. The reconstruction [1] by geodesic erosions $R^*(f,g)$ of f from g is defined by:

$$R^*\left(f,g\right) = E_f^{\infty}\left(g\right) = \lim_{n\to\infty}\left(E_f \circ ... \circ E_f\right)\left(g\right)$$

with $E_f\left(g\right) = \sup\left(g \ominus B, f\right)$.

Reconstruction of a function by its watershed. Let f be a positive and bounded function $(0 \leq f \leq m)$ and let $W(f)$ be its watershed transform. $W(f)$ is the set of the watershed lines of f. Let us build a new function g with $W(f)$:

$$g\left(x\right) = f\left(x\right) \text{ iff } x \in W\left(f\right) \text{ and } g\left(x\right) = m \text{ iff } x \in W^c\left(f\right).$$

This function g is obviously greater than f. Let us now reconstruct f from g. It is easy to see that the minima of the resulting image correspond to the significant markers of the original image f (see Fig. 4).

In fact, the reconstruction fills in (partially) each catchment basin with a plateau at a height equal to the minimum height of the watershed line surrounding this catchment basin. Therefore, if there exists an adjacent catchment basin where the corresponding height is lower than the previous one, the waterfalls will not be symmetrical and the plateau generated in the basin will not be a minimum. Moreover, the watershed transform of $R^*(f,g)$ produces the catchment basins associated with these significant markers.

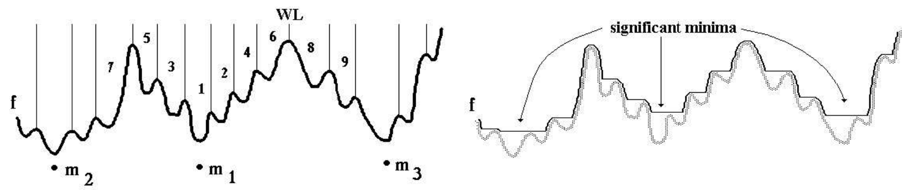

Figure 4. Reconstruction from watershed lines and detection of the significant markers.

Figure 5. The significant minima in an image are used as markers in the gradient watershed image.

4. Comparisons between these hierarchical segmentations

4.1 Waterfalls and mosaic images

When the initial image is the gradient of the mosaic image, the hierarchy settled by the waterfalls is identical to the hierarchy performed by the watershed applied to the graph defined by the gradient of the mosaic image. However, the waterfall is more general and can be applied to any image. This approach is particularly useful for detecting blobs in an image.

The following example (Fig. 5) illustrates this technique. The vehicles on the road are characterized by a front or rear dark region which can be detected by reconstructing the primary image with its watershed and by using the significant minima as markers in the segmentation. The watershed transform of the reconstructed image delineates the extension of the blobs. Then, by using both the significant minima and the watershed lines of this reconstructed image as markers in the watershed of the gradient image, we obtain the final result given at Fig. 5c. Further filtering of the blobs can be made based on their depth.

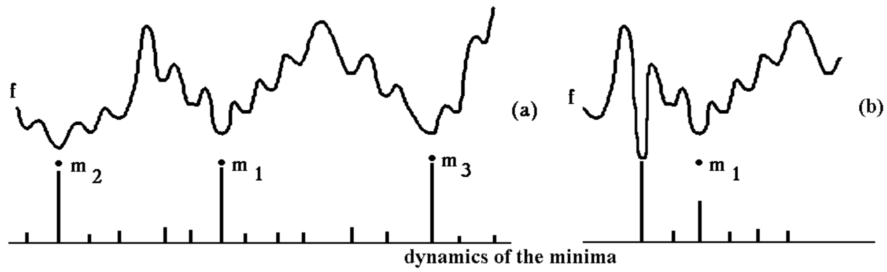

Figure 6. Comparizon betweeen the dynamics and the waterfall algorithm

4.2 Waterfalls and dynamics

The notion of dynamics of a minimum has been introduced by M. Grimaud [3]. The dynamics of a minimum is equal to the height we must climb before reaching any point in the function at a lower altitude than the minimum. If we compare the dynamics and the significant minima of the function at Fig. 6a , we observe a strong similarity between the dynamics and the waterfalls, because the significant minima also correspond, in this example, to minima with high dynamics. This similarity, however, is misleading, as depicted in Fig. 6b. In fact, the two notions are based on two different characteristics: the dynamics is controlled by the relative altitudes of the minima. The waterfalls, on the contrary, are related to the relative heights of the watershed lines. Moreover, the dynamics is more difficult to handle because, in most cases, a threshold is needed to extract the minima with high dynamics. When applied to a gradient image, too, the dynamics give unsatisfactory results because most of the minima of the gradient are at level zero. Therefore, the definition of their dynamics is not simple.

5. Conclusion

In this paper, we have shown that the watershed transformation and the reconstruction of functions can be successfully used in hierarchical segmentation processes. The methodology described here for reducing the over-segmentation is rather simple, it is independent of scale and does not require the setting of any parameter. The final result provides almost homogeneous regions in the image. Further image processing applied on these regions allows us to filter them according to geometrical criteria and enables their possible selection as markers in more complex image segmentations.

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