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From Segmentation to Binarization of Gray-level Images

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Abstract

For some gray-level images, the boundary between the foreground and the background is perceived in correspondence with the locally maximal changes in gray-level through the image. In this framework, this paper proposes a method to extract the objects of interest from an image and, hence, to distinguish the foreground from the background, starting from a partition of the image obtained by means of watershed transformation. The regions that are assigned to the foreground are also hierarchically ranked, depending on their perceptual relevance, so that different representations of the image are possible.
Keywords: Gray-level Images, Segmentation, Binarization.

1. Introduction

Image segmentation is a key step in many applications in pattern recognition, computer vision and image understanding to allow further image content exploitation in an efficient way. The result of segmentation is a partition of a gray-level image into a number of regions, which are homogeneous according to some criteria and belong to either the foreground or the background. The automatic computation of the partition is a relatively easy task. It can be achieved by using techniques largely discussed in the literature, such as the watershed transformation [1]. In turn, the automatic distinction between foreground and background is a complex task, especially when it is based only on the analysis of gray-level information, without involving other features, such as the shape expected to characterize the foreground components. In fact, human observers often classify sets of pixels with the same gray-level in different manners, i.e., as belonging to the foreground, if located in certain parts of the image, and to the background, if located in other parts, depending on the local context.

For images that are perceived as naturally binary, e.g., written documents, the process to distinguish between foreground and background is called binarization, since it refers to the conversion of a gray-level image into a binary image. We will use the term binarization also in this paper, even if we treat images where the gray-levels characterizing the pixels belonging to the foreground are not converted to a unique value, since they play a crucial role for object recognition and classification. The term binarization can be used anyway, since by distinguishing the foreground and the background, a dichotomy of the gray-level image is produced.

In simple cases, binarization can be achieved by thresholding the image [2], i.e., by assigning all the pixels with gray-level lower than a given threshold to either the background or the foreground, and all the remaining pixels to the other set. However, often more sophisticated processes are necessary. This is the case when regions with noticeably different gray-levels are all regarded as of interest, or when regions with the same gray-level can be regarded as belonging to the foreground or to the background, depending on the local context.

Typical examples are biological images, e.g., those including sets of cells or neurons, where foreground pixels are characterized by a variety of gray-levels, depending on their intrinsic nature, their position within the specimen, the illumination, and so on, and the background is not uniform. To obtain a partition of these images, it is convenient to resort to the watershed transformation. The basic idea of this transformation is to detect in the gray-level image a suitable set of seeds from which to perform a *growing process*.

If mainly gray-level distribution is taken into account, the seeds are detected as the sets of pixels with locally minimal gray-level. The growing process associates to each seed all pixels that are closer to that seed more than to any other seed, provided that a certain homogeneity in gray-level is satisfied. Seed selection is a crucial step. In fact, if all sets of pixels with locally minimal gray-level are accepted as seeds, the obtained partition results in a large number of regions, not all perceptually significant. Thus, either the sets of pixels with locally minimal gray-level should be processed to filter out irrelevant seeds, or a region merging step should be considered to reduce the number of partition regions. In any case, once the watershed partition into a reasonable number of regions is available, the assignment of these regions to the foreground or the background has to be accomplished.

In this paper, we propose a binarization method to distinguish foreground and background components for watershed partitioned images. Any identified connected component of the foreground will consist of regions representing individual objects of interest, and for each region a relevance parameter will be given, which weights that region with respect to the most significant part of the same foreground component.

The binarization procedure is based on the integration of the result obtained by a method of watershed segmentation [3], which produces a partition of a gray-level image into regions characterized by quasi-uniform gray-level distribution, and the analysis of the locally maximal changes in gray-level between pairs of adjacent regions.

The analysis is accomplished in three steps, aimed at the identification of foreground components with decreasing perceptual relevance. The first two steps perform a preliminary binarization, while the third step newly examines some regions, temporarily assigned to the background during the second step and, possibly, changes their status. The obtained representation is hierarchical, not only due to the relevance parameter assigned to each foreground region, but also due to the articulation of the process into three steps. Thus, different representations of the same image are available for the user, depending on the desired detail of information.

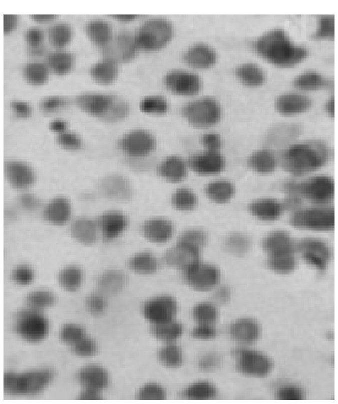


Fig. 1: Running example. Cells of the cerebral cortex of mammalians.

The proposed binarization is an improvement of a method, introduced in [4], from which it differs mainly in the completely new strategy adopted during the second step. The new method produces a more reliable characterization of the regions in terms of their perceptual relevance, by taking into account the position of the regions with respect to the parts of the image where locally strong differences in gray-level occur.

As a running example, we will use part of a gray-level image taken from a specific area, the area TE, in the Rhesus monkey, showing mostly layer II and layer III. In the running example, see

Fig. 1, the foreground is perceived as locally darker with respect to the background. Some regions that the experts classify as belonging to the foreground are lighter than most of the other regions assigned by them to the foreground and their gray-levels do not remarkably differ from the gray-levels in portions of the image that the same experts classify as belonging to the background.

The paper is organized as follows. A preliminary discussion as well as the definitions used throughout the paper are given in Section 2. The method is illustrated in detail in Section 3. There, a running example is used to show the performance of the three steps of the algorithm, and a few more examples, showing the results of the binarization algorithm on different images, are given. Finally, a brief conclusion is given in Section 4.

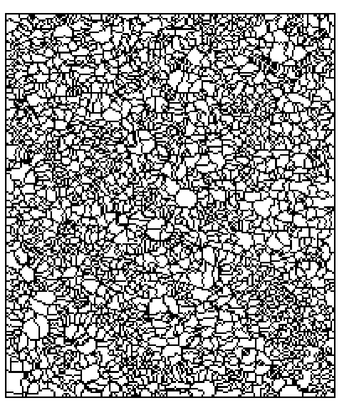
2. Preliminary Discussion and Definitions

In the running example, gray-levels are in the range [0, 255] and the foreground is perceived as locally darker with respect to the background. Thus, the foreground consists of the pixels having locally lower gray-level, according to the generally followed criterion for which the highest gray-level 255 corresponds to white, while the smallest possible value 0 corresponds to black.

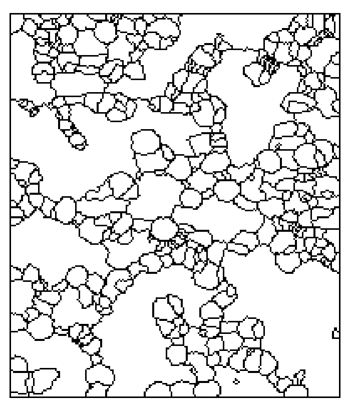
The proposed binarization method starts from a partition of the input image into regions characterized by a common property. This property is a function of the context in which the image is used and can be related to the almost homogeneous gray-level distribution within the region, or to specific geometrical and/or morphological features.

Standard watershed transformation [5,6] can be used to obtain a partition of the input gray-level image. In general, however, these methods produce an excessive number of regions and the literature includes a number of papers dealing with the oversegmentation problem, see e.g., [7-9]. In this paper, to limit oversegmentation, the watershed partition method described in [3] is used, which separates significant regions from non-significant regions according to specific criteria. In [2], the non-significant regions are merged with suitably selected 8-adjacent regions in such a way to produce a perceptually significant image partition. A peculiarity of this method is that significant regions are distinguished from non-significant regions, by using only gray-level information. The obtained watershed partition is, hence, suited to provide the input to the proposed binarization method, which is devoted to the class of images where only gray-level information is taken into account.

The watershed partition of the running example obtained by standard watershed transformation is shown in Fig. 2(a), while the partition produced by the algorithm in [3] is

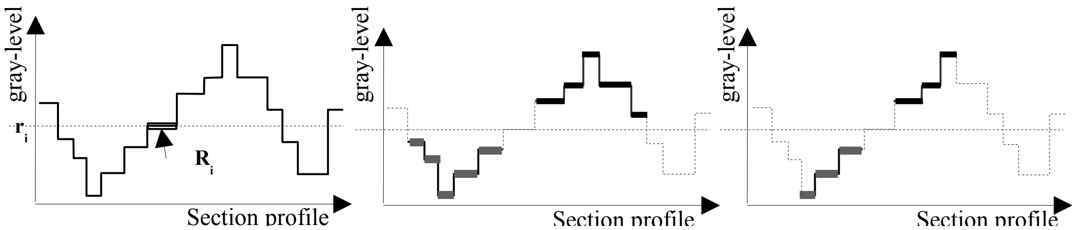


(a)



(b)

Fig. 2: Watershed lines for the running example: standard watershed partition (a), and partition originated by the algorithm [3] (b).



(a) (b) (c)

Fig. 3: (a) Section of the landscape representation of a partitioned image. Plateaux identify regions, (b) the thick black and gray lines represent regions belonging to upper-district and lower-district of Ri, respectively, (c) the thick black and gray lines represent regions belonging to upper-slope and lower-slope of Ri, respectively.

shown in Fig. 2(b). The number of regions identified by the standard partition method is 2377. This number is reduced to only 371 significant regions by the method used in this paper.

An identity label is associated with each region of the partition by the watershed transformation, to individually treat the various components and to count them. The image partitioned into N regions is represented by a graph with N nodes. Each node R_i , $i=1,2,\ldots, N$ corresponds to a region and the arcs linking the nodes describe the adjacency relations among regions. In the following, the terms node and region will be used interchangeably.

A parameter, r_i, is assigned to each node R_i. This parameter identifies a *representative gray-level value* for the region R_i. The value r_i will be used, in the proposed binarization method, to assign the regions of the partition to one of the two categories foreground and background. To compute r_i, we take into account that any region of the partition includes pixels with different gray-levels. In particular, the following two criteria to compute r_i are combined:

- r_i is the most frequent gray-level in the region, or – if more gray-levels have the same maximal occurrence in the region, is the average of these gray-levels
- r_i is the average of all the gray-levels in the region

It has been experimentally found that it is convenient to use the first criterion when the computed maximal occurrence is at least 30% of the total number of pixels in the region, and the second criterion otherwise. Naturally, two adjacent nodes may be characterized by the same value of r_i. When this is the case, the two nodes are merged to form a single node. The gray-levels in the original image are replaced by the ri values representing the regions, so obtaining a smoothed image.

A useful interpretation of the smoothed partitioned image is given by its 3D landscape representation, where each region R_i of the partition is seen as a plateau at altitude r_i. According to this interpretation, locally higher representative gray-levels correspond in the landscape to mountains and hills, while locally lower representative gray-levels correspond to valleys, see Fig. 3(a), where a vertical section of the 3D landscape is shown.

A sequence R_1, R_2,…, R_f of distinct nodes of the partitioned image is a path from R_1 to R_f, if R_i is adjacent to R_{i-1} for $i=2,\ldots,f$. A path from R_1 to R_f is said to be *monotonically increasing* (*decreasing*) if $r_{i-1} \leqslant r_i$ ($r_{i-1} \geqslant r_i$), for $i=2,\ldots,f$.

A node R_f is said to belong to the *lower-district* (upper-district) of a node R_1 if there exists a path from R_1 to R_f, constituted only by nodes whose representative gray-value is smaller (greater) than or equal to r_1. The set of nodes belonging to the lower-district and upper-district of R_1 defines the *district* of R_1, see Fig. 3(b).

A node R_f is said to belong to the *lower-slope* (*upper-slope*) of R_1 if there exists a *monotonically decreasing (increasing)* path R_1 to R_f. The set of nodes belonging to the lower-slope and upper-slope of R_1 defines the slope of R_1, see Fig. 3(c).

Besides r_i, a second parameter, s_i, called the *relevance parameter*, will be used to hierarchically rank regions, depending on their perceptual relevance. More details on s_i are given in Section 3. In principle, ranking can be done for regions of both the foreground and the background. In this paper the description is limited to ranking foreground regions only. For any such a region, the parameter s_i will assume values 1,2,3,... , where 1 indicates the maximal relevance.

3. The 3-step Binarization Procedure

As already indicated, gray-level images are considered where one of the two sets, the foreground for the running example, is perceived as characterized by locally lower intensity, consistently throughout the image. The proposed binarization method is inspired by visual perception. It starts from a watershed partition, where the regions forming the mosaic image are distinguished from each other, but have not yet been assigned to either the foreground or the background.

The process requires three steps. The first step assigns to the foreground and to the background regions that without any doubt belong to these categories. These regions are those representing valleys and peaks in the landscape. The second step provides a temporary assignment of the not yet assigned regions to one of the two categories. Since the boundary separating the foreground from the background is perceived in correspondence with strong differences in gray-level, we base the second step on the computation of the difference between the representative gray-level values of all pairs of adjacent regions. In particular, if two adjacent nodes R_i and R_j are such that the difference $\delta_{ij}=|r_i-r_j|$ is the largest possible one, the two nodes are likely to belong one to the foreground and the other to the background. The second step terminates when all regions have been assigned. The third step newly examines some of the regions temporarily assigned to the background during the second step and possibly changes the status of a few of them provided that specific conditions are satisfied.

3.1 Step 1 of Binarization

The first step of the process regards the assignment to the foreground and the background of regions respectively representing valleys and peaks in the landscape. These regions are respectively characterized by locally minimal and locally maximal representative gray-levels. These nodes are globally identified in the graph, independently of the evaluation of how large the difference in gray-level is with respect to the adjacent nodes. However, if the difference in altitude between a valley (peak) and the peaks (valleys) including it is not sufficiently large to perceive the valley (peak) as standing out against the surrounding peaks (valleys), assignment of such a valley (peak) to the foreground (background) should not be accomplished. To this aim, once valleys and peaks have been detected, a smoothing process is applied to remove non significant peaks. In detail, each peak node which is adjacent to a valley node and whose altitude differs less than an a priori fixed threshold from the altitude of the adjacent valley is changed its representative gray-level value, to that of the adjacent valley. Whenever a peak is lowered, its adjacent valley node is newly checked to verify if it is still a valley. The threshold value is set depending on image domain. Only valleys and peaks surviving the smoothing process are respectively assigned to foreground and background.

The regions assigned to the foreground do not necessarily have the same perceptual relevance, as this depends on the comparison between their altitude and the altitude of the peaks. In particular, it may happen that some valley nodes are characterized by representative gray-

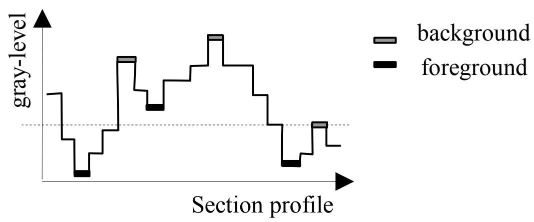


Fig. 4: Peaks and valleys in a section of the landscape representation. The dashed line passes through the smallest gray-level identifying a peak.

levels higher than the representative gray-levels characterizing some peak nodes. This happens, for example, in correspondence with parts of the specimen that are slightly out of focus.

For illustrative purpose, see Fig. 4, where the profile of a section of a landscape image representation is shown. The dashed line identifies the altitude of the shortest peak (i.e., the smallest gray-level characterizing a regional maximum); thick gray and black lines are used to color the plateaux respectively denoting peak nodes and valley nodes. Any valley in the landscape is worth to belong to the foreground. However, if its representative gray-level is higher than the gray-level characterizing a peak, which is obviously assigned to the background, the perceptual relevance of that valley is smaller than the perceptual relevance pertaining other valleys with representative gray-level lower than the gray-level of every peak.

Two possible values are ascribed to the relevance parameter s_i. For each detected valley R_i s_i set to 1 if the altitude r_i is smaller than the minimum altitude of all detected peaks, while s_i is set to 2 otherwise.

Fig. 5: Foreground regions detected after Step 1.

In Fig. 5, the regions of the partition of the running example that are ascribed to the foreground at the end of Step 1 are shown in two dark gray-tones. The darker gray-tone is used for regions with $s_i=1$, while the lighter gray-tone is for regions with $s_i=2$.

3.2 Step 2 of Binarization

The second step regards the assignment to the foreground and the temporary assignment to the background of unassigned regions placed along slopes in the landscape. The process is iterated as long as unassigned regions exist.

For each node R_i assigned to the foreground during each iteration, the relevance parameter s_i is set to $n_{ij}+s_j+1$, where n_{ij} is the minimum number of foreground regions separating R_i from a region, say R_j, assigned to the same foreground component during a previous iteration of Step 2 or during Step 1, and s_j is the perceptual relevance of R_j.

At each iteration, only pairs of adjacent nodes (R_i, R_j) with at least one unassigned node are considered. For any such a pair, let us assume that $r_j > r_i$, and compute the value $\delta_{ji}=r_j-r_i$. Let $\Delta=\max\{\delta_{ji}\}$ be the maximal difference in gray-level for all these pairs. Since the boundary between the foreground and the background is perceived as placed wherever strong differences in gray-level occur, a transition from foreground to background is likely to exist in correspondence with the nodes of any pair (R_i, R_j) for which $\delta_{ji}=\Delta$.

Let T be the set of pairs of nodes with $\delta_{ji}=\Delta$. The node R_i (R_j) of any pair (R_i, R_j) of T will be termed bottom (top) node of T. Let $\max_{\text{bottom}}$ and $\min_{\text{top}}$ be the greatest and the smallest representative gray-level values associated to the bottom nodes and to the top nodes of the pairs in the set T, respectively. These values are used to decide the process to be accomplished for the assignment to the foreground and the background of the regions placed along slopes in the landscape. At each iteration, two cases are possible.

Case 1: $\max_{\text{bottom}} < \min_{\text{top}}$

Every bottom node of T (including the bottom node with the highest representative gray-level

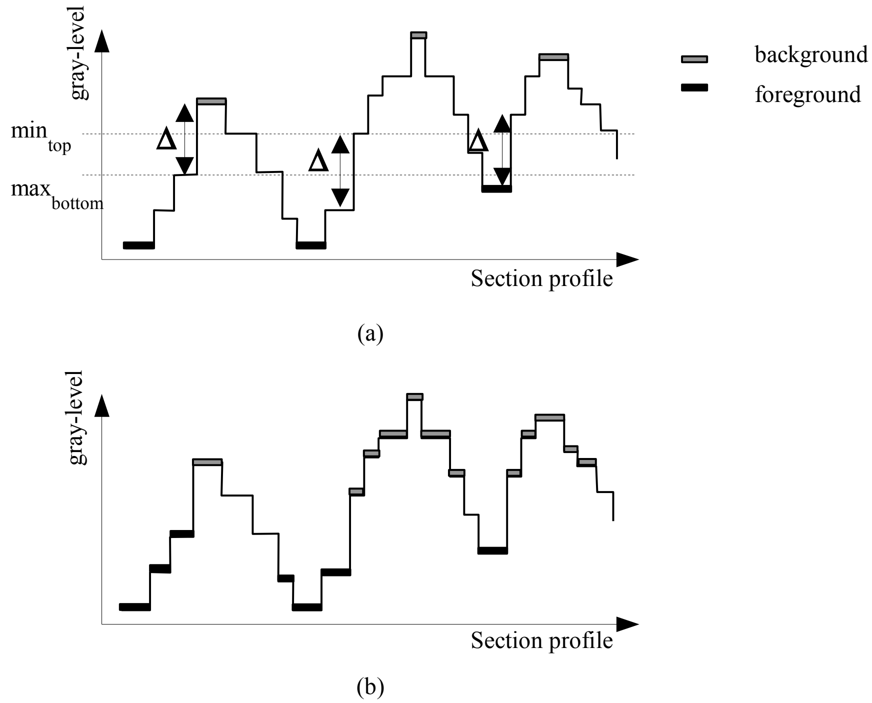


Fig. 6: Case 1. A section profile before (a), and after (b), an iteration of Step 2.

$\max_{\text{bottom}}$) corresponds to a region that, in the landscape, has altitude smaller than the altitude of each region corresponding to a top node of T (including the top node with the smallest representative gray-level $\min_{\text{top}}$). An example of such a configuration is shown by the section profile in Fig. 6(a). Three pairs of adjacent nodes are characterized by the maximal difference in gray-level Δ ; the dashed lines pass through the top node and through the bottom node, which, in these three pairs, have the smallest and the highest gray-level, respectively.

In this case, foreground and background assignments can be done without any further checking. We ascribe to the foreground (background) every bottom (top) node R_s (R_k) of T; moreover, we assign to the foreground (background) every unassigned node R_h belonging to the lower-district (upper-district) of R_s (R_k). With reference to Fig. 6(a), at the end of the current iteration the three bottom (top) nodes of T result to be assigned to the foreground (background) together with the relative lower-districts (upper-districts). See Fig. 6(b). Some nodes still result as not yet assigned. These are the nodes that do not belong to the lower-districts or the upper-districts of the nodes of the pairs of T. Step 2 is, then, iterated: Δ is newly computed and a new set T is identified. Obviously, the value of Δ computed at this iteration is smaller than the value computed at any previous iteration. This guarantees that Step 2 will terminate in a finite number of iterations.

Case 2: $\max_{\text{bottom}} \geqslant \min_{\text{top}}$

At least one bottom node R_s of T corresponds to a region which has altitude greater than or equal to the altitude of at least one region represented by a top node R_k of T. We note that R_s and R_k may be placed along the same slope and, in this case have different representative gray-levels; in turn, R_s and R_k may be placed along different slopes, and, in this case, they can have different representative gray-levels, but can also be characterized by the same representative gray-level.

An example is shown by the section profile in Fig. 7(a), where T includes three pairs. Two pairs are along the same slope, while the third pair is placed along a different slope. For one of

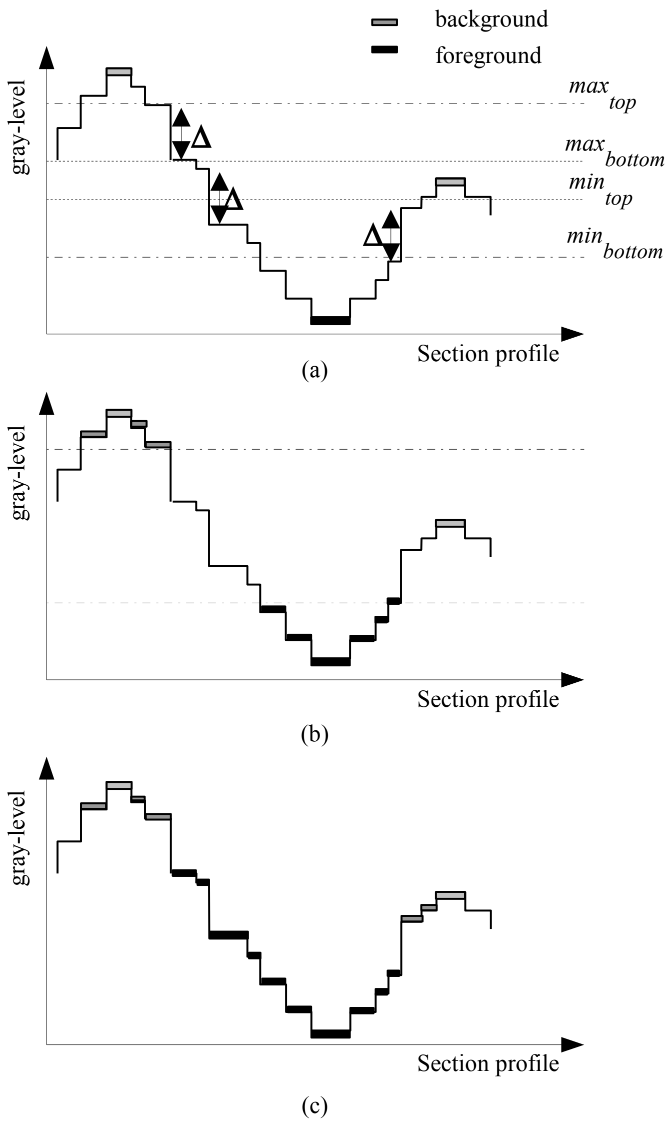


Fig. 7: Case 2. A section profile before an iteration of Step 2 (a), "safe" assignment, done during the iteration after the computation of $\max_{top}$ and $\min_{bottom}$ (b), final assignment accomplished during the iteration (c).

the two pairs of T placed along the same slope, the bottom node has higher gray-level with respect to the top node in the pair placed along the same slope; for the third pair of T, located alone along another slope, the top node has lower gray-level with respect to one of the bottom nodes in the other two pairs of T.

In this case, assignment cannot be accomplished by the same procedure used for Case 1, since some nodes in the pairs of T can be equivalently assigned to foreground or to background. This is the case for bottom (top) nodes characterized by gray-level larger than $\min_{top}$ (smaller than $\max_{bottom}$). Any such a node can be interpreted as belonging to the foreground and to the background at the same time. In fact, such a bottom (top) node should be assigned to the foreground (background), by taking into account that its gray-level is smaller (larger) than the gray-level of the top (bottom) node in the pair. At the same time, that bottom (top) node should be assigned to the background (foreground), by taking into account that its gray-level is larger than $\min_{top}$ (smaller than $\max_{bottom}$).

Among the pairs in T, we first assign the nodes for which decision can be taken in a unique way. To this purpose, the minimum value is computed, $\min_{bottom}$, among the gray-levels of all bottom nodes in T, and the maximum value, $\max_{top}$, among the gray-levels of all top nodes in T. Any bottom (top) node R_s (R_k) with $r_s=\min_{bottom}$ ($r_k=\max_{top}$) can be assigned without any doubt to the foreground (background). For any such a bottom (top) node R_s (R_k) assigned to the foreground (background), we also assign to the foreground (background) every unassigned node belonging to the lower-district (upper-district) of R_s (R_k), exactly as done in Case 1. See Fig. 7(b), where the bottom (top) node with gray-level $\min_{bottom}$ ($\max_{top}$) as well as its entire lower-district (upper-district) has been assigned to the foreground (background).

After this "safe" assignment, the bottom nodes of T are examined in decreasing order of their representative gray-level value. Only pairs (R_i, R_j) of nodes in T, out of which at least one node is still unassigned, are taken into account. Let R_s be the bottom node such that r_s is the maximum among the gray-levels of all bottom nodes of T and let (R_s, R_t) be the pair of T including R_s. We ascribe R_s (if still unassigned) to the foreground and R_t (if still unassigned) to the background; moreover, we assign to the foreground (background) any unassigned node R_k belonging to the lower-slope (upper-slope) of R_s (R_t). Note that differently from Case 1, only the lower-slope (upper-slope) is considered, instead of the lower-district (upper-district).

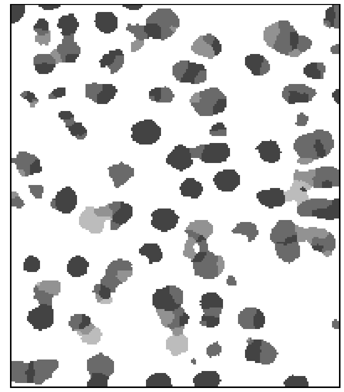


Fig. 8: Foreground components after Step 2.

With reference to Fig. 7, we note that the pair (R_s, R_t) that is analysed first is the pair where the top node R_t has gray-level $\max_{top}$, and has already been assigned to the background by the "safe" assignment. After R_s is assigned to the foreground, all the unassigned nodes with non increasing gray-level, i.e. placed along the lower-slope, are also assigned to the foreground. Since only the lower-slope of R_s is considered, assignment to the foreground will not include also the unassigned nodes with gray-level smaller than or equal to r_s, that are placed along the slope climbing towards the third, isolated, pair of T. In fact, these nodes belong to the lower-district of R_s, but not to its lower-slope and will be assigned when the third pair of T will be examined. The upper-slope of R_t does not include unassigned nodes. Thus, the next pair of T is examined, in decreasing order of the gray-level of the bottom nodes. This pair is the third pair of T, placed alone along a slope. In fact, the second pair of T, along the slope of the pair just processed, has both nodes already assigned.

Once all the pairs of nodes in T, out of which at least one node is still unassigned have been processed, the current iteration terminates. The result at the end of the current iteration can be seen in Fig. 7(c).

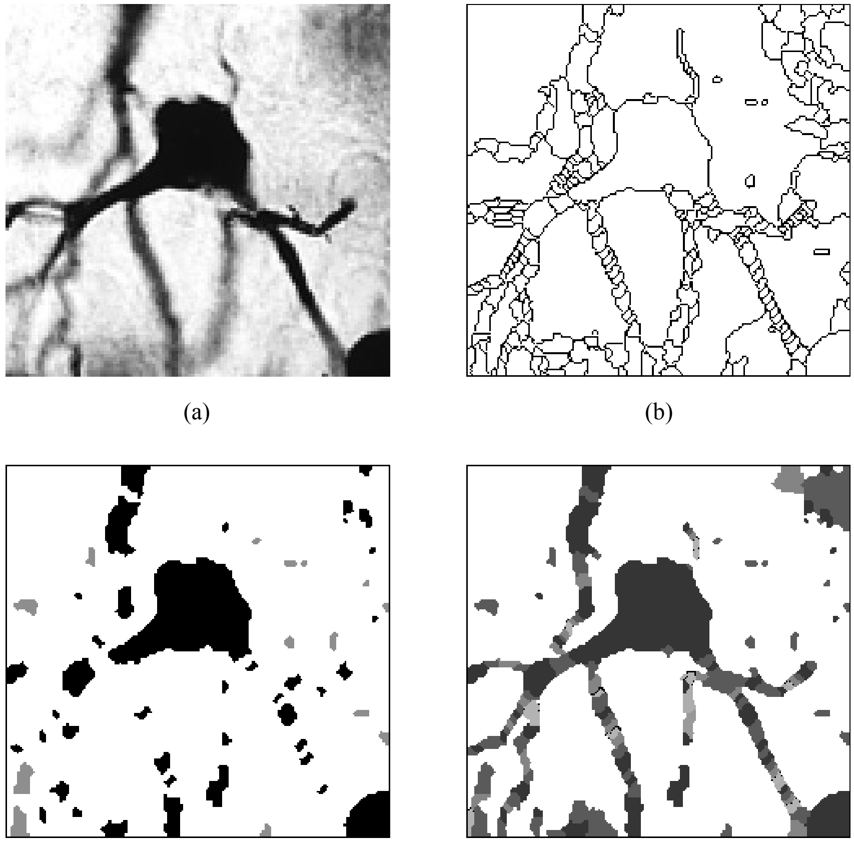
As it has been already pointed out, Step 2 is iterated until all nodes are assigned to either the foreground or the background. Our local process favours the assignment of most of the slope to the foreground; however, we point out that the nodes belonging to lower-districts/slopes are assigned higher and higher relevance parameter and are, hence, regarded as less and less significant. The result at the end of Step 2 for the running example is shown in Fig. 8, where different gray-tones account for different values of the relevance parameter. Lighter tones denote less significant regions.

We point out that also in [4] Case 1 and Case 2 were taken into account, but the procedures adopted to treat the two cases were different. In particular, after a bottom (top) node R_s (R_k) of T was assigned to the foreground (background) in Case 1, a global assignment to the foreground (background) was also performed for all the nodes of the graph corresponding to the regions with altitude smaller (greater) than or equal to r_s (r_k). This assignment was accomplished without checking whether such nodes were actually placed along the districts of R_s (R_k). Obviously, the computational cost of that process is smaller than the cost associated to the new process, where the districts associated with a given node have to be identified. On the other hand, the new method outperforms the method presented in [4].

Another example is shown in Fig. 9. In this case, the input image represents a pyramidal neuron of bovine cerebral cortex, stained with Golgi method. The perceived foreground includes a main blob-shaped body as well as a number of protruding thin elongated regions.

3.3 Step 3 of Binarization

At the end of Step 2 all nodes result to be assigned, at least temporarily, to either the foreground or the background. During Step 3, the status of some nodes assigned to the background in Step 2



(a) (b)

(c) (d)

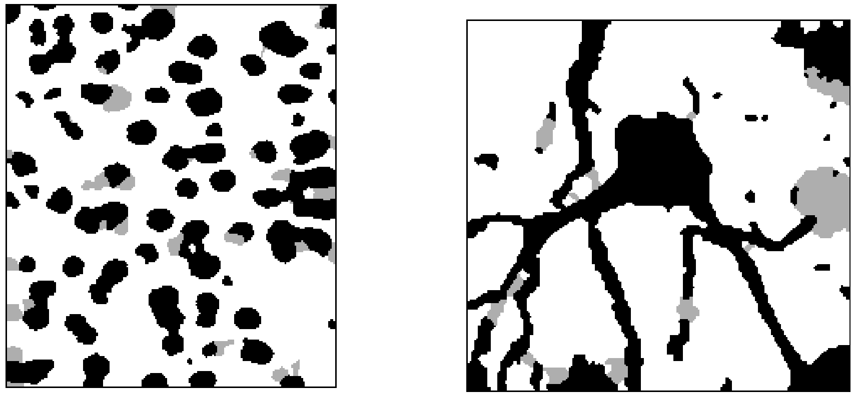
Fig. 9: Pyramidal neuron of bovine cerebral cortex (a), watershed lines (b), result after Step 1 (c), and Step 2 (d).

is changed. Any background node that we consider as candidate to change its status is, at least partially, adjacent to some foreground components and is characterized by a representative gray-level that is the minimum among the representative gray-levels pertaining its neighbouring background nodes. Of course, the gray-level of the candidate node is larger than the gray-level of the foreground nodes it is adjacent to.

There are two options that the user selects depending on his/her needs. In case of images like the running example, where the shape and the size of the individual object components is roughly similar, the status of a candidate node is changed only if the change does not cause a topology change in the image (Option 1). In fact, status modification is done, in this case, with the purpose of favouring region growing without merging individual foreground regions into clusters. In turn, when the shape and size of the object components largely differ, as it is the case for the example shown in Fig. 9, a candidate node is assigned to the foreground only if this assignment causes a topology change (Option 2).

The perceptual relevance parameter s_i of a node reassigned during Step 3 is set by the same procedure already described for Step 2.

The results obtained at the end of Step 3 are illustrated in Fig. 10. In particular, Fig. 10(a) shows the result obtained for the running example with Option 1. In turn, in Fig. 10(b), the result by using Option 2 for the image in Fig. 9(a) is shown. Only two gray-tones are used for simplicity. The light gray-tone denotes regions assigned to the foreground during Step 3, while the dark gray-tone denotes regions assigned during Steps 1 and 2.



(a) (b)

Fig. 10: Results after Step 3. Option 1 (a), and Option 2 (b), have been respectively used for the running example and for the image in Fig. 9(a).

A few more examples showing the performance of our method can be seen in Fig. 11.

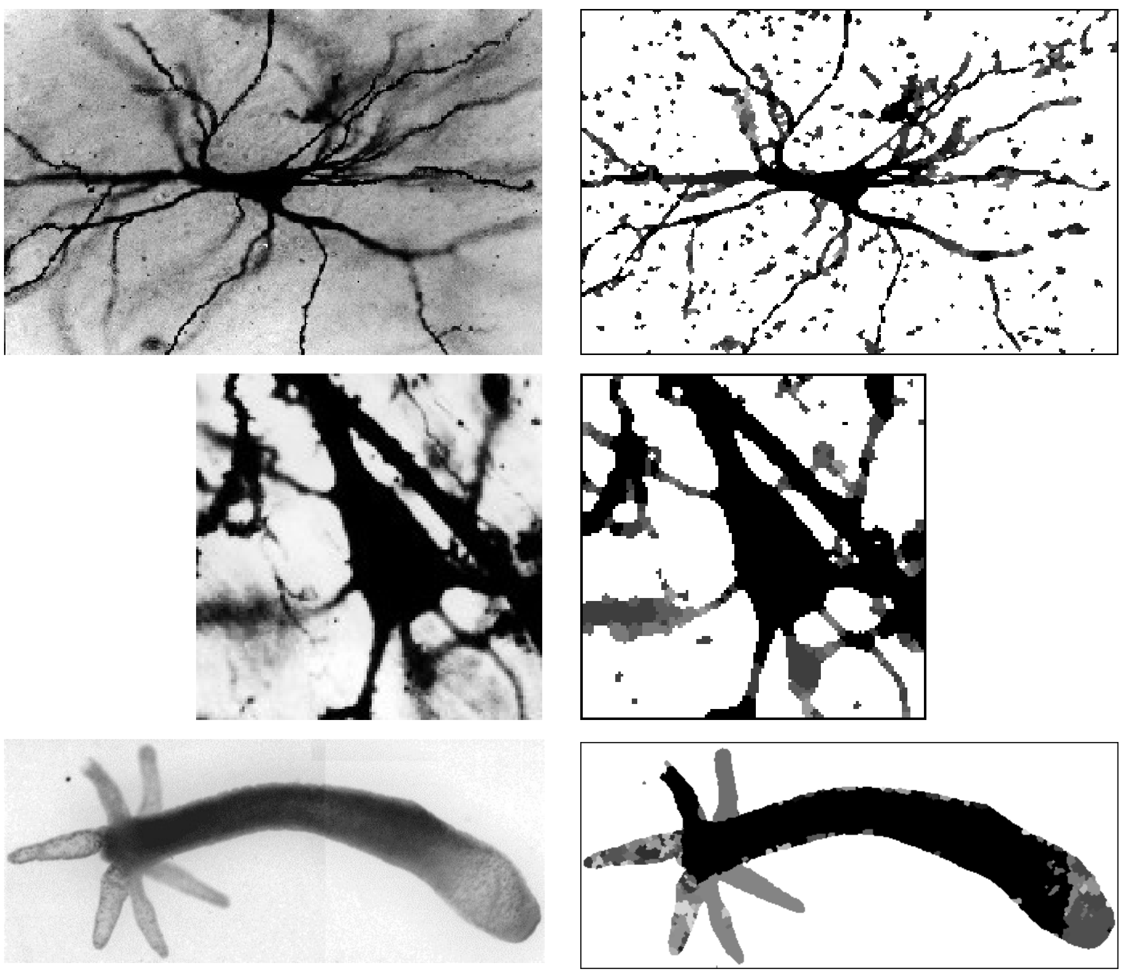


Fig. 11: Set of biological input images (left column) and the corresponding binarizations (right column). From top to bottom, pyramidal neurons of bovine cerebral cortex, pyramidal neurons of rabbit cerebral cortex, Hydra vulgaris.

Most of the images that we have used to test our process belong to a set of biological images with average size of 512x512. The proposed binarization method has been also applied to images belonging to different classes to check its validity. For example, it was applied to face images with the aim of identifying the most relevant face parts (eyes and lips) in the framework of face recognition.

4. Conclusion

A method to identify foreground components in a partition of a gray-level image, obtained by watershed segmentation has been discussed. Both global and local assignment processes are taken into account. A global process is done only during Step 1. In fact, this step is based on the computation of valleys and peaks, which be done with high degree of confidence. Local processes are used within Step 2, during which regions placed on the slopes of the landscape are assigned. During Step 2, the pairs of adjacent nodes having maximal difference in gray-level are identified. These nodes are assigned together with the nodes placed along their lower and upper-districts/slopes. A local process is also accomplished during Step 3. Notwithstanding the method mostly requires local processes, the whole computational cost is limited to a few seconds, since all computations are accomplished on a graph whose nodes correspond to the regions of the partitioned image.

An interesting feature of the proposed method is the fact that foreground regions are hierarchically ranked by means of the parameter s_i. Two different kinds of hierarchy can be seen. The first hierarchy ranks the regions of the foreground components in three main levels, since three are the steps of the process. Foreground regions detected at Step 1 are the most perceptually relevant, as they correspond in the landscape representation to significant valleys; regions detected during Step 2 have smaller relevance, since they correspond to nodes placed along the slopes of mountains and hills; finally, regions detected during Step 3 are the less significant ones, as they were actually assigned to the background during Step 2. The second hierarchy is determined within each step. It is based on gray-levels within Step 1, and on the distance, expressed in terms of the number of nodes along the slope, within Steps 2 and 3.

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