An improved watershed algorithm for image segmentation

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Abstract

Watershed transform is a key operator in image segmentation algorithms. However, the computation load of watershed transform is too large for real-time applications. Previously published watershed segmentation algorithms required at least three global synchronization points: minima detection, labelling and flooding. This paper presented an algorithm of watershed transformation based on opening-closing operation and distance transform. It improved the classical watershed segmentation algorithm based on distance transform, overcoming over segmentation. The experiment result demonstrated that this method for segmentation inherits the advantage of watershed algorithm based on distance transform that it successfully segment out each dowel in the image bringing convenience to computer vision and auto-counting of dowels. It also overcame over-segmentation existed in traditional watershed segmentation preserving the original edges of each dowel in the image completely. This algorithm can be combined with any image segmentation algorithm to give more precise segmentation results. An example is also shown by combining a background registration and change-detection-based segmentation algorithm with Watershed. This new video segmentation algorithm can give accurate object masks with acceptable computation complexity.

Keywords: watershed transform, image segmentation, automatic segmentation method

1 Introduction

Image segmentation is the process of building a partition of the image into connected regions, such that picture elements (pixels) of the region are homogenous according to some criterion (gray value, motion, etc). In this paper, we will focus on the watershed transform which is a mathematical morphology method for segmenting images. Most of the time, the watershed transform is applied to a gradient image for extracting homogeneous regions with respect to luminance. This gradient image is considered as a topographic relief, and watershed segmentation amounts to extracting significant basins in this relief. Watershed is a fundamental approach in a variety of fields, like image compression, coding, and analysis. It is used in telecommunication, biomedical, physics, satellite picture analysis, fast imaging system, etc. However, watershed segmentation is a computationally intensive task.

Watershed transform, which can separate an image into many homogeneous non overlapped closed regions, has been widely applied in image segmentation algorithms. It is also applied to image sequences as a core operator of video segmentation, which is a key technique in MPEG-4 content-based encoding systems. Video segmentation algorithms with watershed transform are taken as mainstream since they can generate object masks with accurate boundaries.

Many watershed algorithms have been proposed. Vincent and Soille proposed a watershed algorithm using immersion simulations. With sorting before the flooding process and with priority queue, this algorithm is dramatically faster than any former ones. Beucher and Meyer's algorithm also uses immersion simulations. Two types of algorithms are included: one creates watershed pixels and the other produces a complete tessellation of an image. An ordered queue is used in this algorithm, whose concept is similar to that of Vincent and Soille's algorithm; however, the minima of the input image need to be detected and labeled first, thus increases the complexity of this algorithm. Dobrin et al. proposed a fast watershed algorithm named split-and-merge algorithm. It can solve the isolated area problems of the former two algorithms when they are employed to create watershed pixels. Although the results obtained are more correct, it is more complex than the other two algorithms. Moreover, watershed transform for video segmentation is often required to produce a tessellation of an image, where the isolated area problem would not occur. Moga et al. proposed a watershed algorithm suitable for parallel implementation. With parallel computation, the watershed algorithm can be further accelerated. However, it is also complex and requires a powerful platform, which is impractical for general cases.

Several implementations of the watershed algorithm can be found in the literature: Sequential algorithms by immersion and other algorithms based on topographical distance, like the Hill-Climbing algorithm. Efficient implementations and parallelization of these algorithms have to cope with the problem of non-minimum plateau, which can be solved by using hierarchical FIFO (First-In-First-Out) queues, or by a lower completion of the input image. A recent implementation of a Hill-Climbing

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algorithm using FIFO queues is presented. The paper surveys approaches for a parallel implementation of the watershed algorithm: most of them are based on the Hill-Climbing algorithm, distributing the image in blocks over the set of processors implemented on a Parsystec supercluster 128 or a Cray3D. The lack of scalability, of these implementations is mainly due to the need for a global synchronization between processors for local minima detection, non-minimum plateau flooding, or lower completion. A fine grain parallelization was also proposed, using an associative net model, although the minimum detection is a prerequisite.

This paper proposes an improved watershed algorithm for image segmentation on the basis that watersheds are highly related to original frame data. It updates watersheds instead of recalculating watershed transform frame by frame. The watershed process can be accelerated, and the results are almost the same as those of conventional watershed algorithms. Furthermore, the segmentation results can be further improved with the intra-inter watershed scheme. In this paper, the watershed algorithm is programmed as a set of concurrent communicating iterative programs that are efficiently mapped onto an asynchronous parallel architecture. This idea was previously suggested and has also more recently been studied with the paradigm of Asynchronous Cellular Automata (ACA), i.e., a lattice of finite state machine interconnected to its nearest neighbours. The general specification of the watershed algorithm we propose is mapped onto an asynchronous processors array which enables us to derive a set of architectures, ranging from a fine grain processing (one finite state machine per pixel), to coarser implementations (a complex finite state machine or program which is able to process several pixels). In the case of fine granularity, this ACA leads to an implementation similar to the associative mesh.

2 Related works

The watershed segmentation technique has been widely used in medical image segmentation. Examples include the work presented in [1, 2], which make use of the watershed transform to segment grey and white matter from magnetic resonance (MR) images. The algorithm originated from mathematical morphology that deals with the topographic representation of an image [3, 4]. The set of pixels with the lowest regional elevation corresponds to the regional minimum. The minima of an image are the groups of connected pixels with their grey level strictly lower than their local neighbouring pixels. The rainfall simulation [3] describes that when rain falls onto the surface, any rain drop reaching a point in the surface will flow along its steepest descent until it reaches a minimum. The paths of pixels, which converge towards a common minimum, constitute a catchment basin. Watersheds are the elevated areas that divide the different catchment basins. The partitions, which we aim to obtain, are the catchment basins, and the boundaries between the partitions are the watersheds. Advantages of the watershed transform include the fact that it is a fast, simple and intuitive method. More importantly, it is able to produce a complete division of the image in separated regions even if the contrast is poor, thus there is no need to carry out any post-processing work, such as contour joining. Its drawbacks will include over-segmentation and sensitivity to noise [2]. There has also been an increasing interest in applying soft segmentation algorithms, where a pixel may be classified partially into multiple classes, for MR images segmentation [5-7]. The fuzzy C-means clustering algorithm (FCM) is a soft-segmentation method that has been used extensively for segmentation of MR images [8]. However, its main disadvantages include its computational complexity and the fact that the performance degrades significantly with increased noise. K-means clustering algorithm [9, 10], on the other hand, is a simple clustering method with low computational complexity as compared to FCM. The clusters produced by K-means clustering do not overlap.

In past few decades, various segmentation techniques have been pro-posed. Generally, they are based upon two basic properties: similarity and discontinuity. Pixel similarity gives rise to region-based segmentation [7-9], whereas pixel discontinuity gives rise to edge-based segmentation [10-12]. These two traditional techniques may be able to get good result for some simple images. However, it is always difficult to achieve desired result for HSRI segmentation due to the complexities of the landscape structure on the image. While textures in objects, such as forest, are always detected as spurious object boundaries, which cause over-segmentation; the edges between the farm fields may appear to be obscure that may induce under-segmentation. With regard to these problems, many works have been done. Some researchers integrated texture in segmentation to avoid the over segmentation of spectral heterogeneous objects [13]. In this strategy, the texture calculation before segmentation is time-consuming. Moreover, the texture boundary effect [14] may induce the location uncertainty of the extracted object boundaries. Some researchers proposed to segment image at multistage, then select and merge the optimal scale of segmentations to achieve good result [15]. However, how to select the optimal scale for different type of ground objects and merge them is still a difficult task that needs further research. Some researchers tried to integrate edge information into segmentation to get more accurate object boundaries [16]. This strategy takes the advantage of both region-based and edge-based segmentation techniques and is more practical for the quick and effective processing of large size data.

3 The proposed method

3.1 BASIC IDEA OF THE PROPOSED METHOD

Watershed algorithm is usually applied to the gradient image. Imagine the gradient image is a topographic surface, a hole is drilled in each minimum of the surface, and water is flooded into different catchment basins from the holes. As a result, the water starts filling all catchment basins, which have minima under the water level. If two catchment basins would merge as a result of further immersion, a dam is built all the way to the highest surface altitude and the dam represents the watershed lines. This flooding process will eventually reach a stage when only the top of the dam is visible above the water line. The result is a tessellation of the input image into its different catchment basins, each one characterized by a unique label.

The method is a two-stage process, including the extraction of marker image and the labelling of pixels (flooding). Markers are a set of components marking flat regions of an image, i.e., each marker indicates the presence of an object. If the object interiors (markers) are set to 1, and the uncertainty areas are set to 0, we get a binary marker image. It contains a set of components (markers) marking the core regions and a large number of pixels may remain unassigned. The next step is then to label the unassigned pixels by the extended watershed algorithm dealing with markers to get the final partition. It has the advantage that segmented results can have coherent regions, link edges, no gaps due to missing edge pixels. However, applying this method to HSRI segmentation, the noises or textures on the image are usually labelled as the pseudo-local minimum regions and result in over-segmentation. To reduce over-segmentation, we make some improvements to the marked-based watershed segmentation algorithm. First, a regional adaptive marker extraction method is proposed. The marker image is created from gradient image by binary processing. Instead of using a fixed threshold, such as H-minima algorithm, a threshold image, on which the threshold of each pixel is statistically estimated and used for binarization. Because it considers the complex grey level distribution of HSRI, the extracted makers are more coincide with the real objects. Then, the image labelling scheme in the Meyer's algorithm is implemented by using one queue and one stack data structure. This scheme can largely save memory cost and make it applicable to large image. The overall framework is shown in Figure 1.

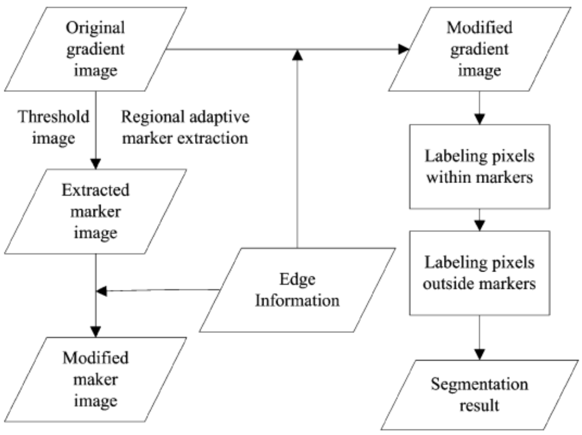

FIGURE 1 Framework of segmentation

3.2 HYBRID SCHEME

Although the segmentation results are almost the same as those of the conventional watershed algorithms, the proposed algorithm may introduce error in the following conditions. First, change detection is not sensitive enough. Second, the minimum of a catchment basin is included in UA, and a part the catchment basin is not included. Third, the scenes change a lot. The error will propagate in the proposed predictive watershed algorithm. The error propagation can be interrupted by inserting a frame where watersheds are generated with the conventional algorithm. These watersheds do not need information from the previous frame, so we have the term "intra watershed" (I-Water-shed). The I-Watershed and P-Watershed hybrid scheme, called IP-Watershed, is illustrated in Figure 2.

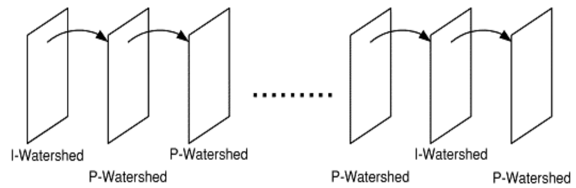

FIGURE 2 I-Watershed frames are inserted to avoid error propagation of Watershed

It can accelerate the watershed process and maintain accuracy at the same time. The time to insert an I-Watershed can be decided with the following two strategies to interrupt the error propagation. To deal with the first and the second error conditions described above, we can insert an I-Watershed frame after a fixed number of P-Watershed frames. The fixed interval to insert an I-Watershed frame depends on the threshold and the error rate required for the applications. After is decided, the error accumulation behaviour, which is the amount of increasing error for each frame, is also decided. An I-Watershed should be inserted when the accumulated error exceeds the required error rate. The less the error accumulated in each frame, the longer the interval to insert an I-Watershed frame; the tighter the error requirement, the shorter the interval. On the other hand, to deal with the third condition, scene change condition, the error rate is monitored in each frame. An I-Watershed frame is inserted dynamically when the monitored error rate exceeds a required value. These two strategies can be employed simultaneously to interrupt error propagation effectively.

3.3 LABELLING PIXELS

The labelling of pixels is the process of assigning each pixel a unique identity (ID). There are two often-used pixel labelling methods.

1) The first method uses the individual markers as the local minima in the gradient image. It filters out the undesired minima of the gradient image, and applies the traditional watershed segmentation on the revised gradient image.

2) The second method suppresses unwanted minima during labelling process. The marker based immersion type watershed algorithm proposed in literature, performs the flooding process directly on the original gradient image. It was realized by using the data structure of hierarchical circular queues. The hierarchical circular queues are a set of queues with different priorities, each queue is a first-in first-out data structure. The priority of each pixel in the gradient image is defined as the reciprocal of its gradient value. This implies that a high (low) priority is assigned to a pixel with low (high) grey-level value. To save memory cost for large image segmentation, we proposed to use a data structure of only one queue and one stack to store the temporary data in image labelling. It can largely reduce the memory cost. The pixels are first sorted in a descending order of priority. Then the possible neighbour labelled pixel of each unlabelled pixel is searched by seed tracing to identify the label ID for the current processing pixel. In the search process, one queue (QU) and one stack (ST) are used. In labelling pixels, the pixels within marker and the pixels outside makers are labeled successively.

During labelling the pixels outside the markers, the pixels labeled lastly are more possible to be on the watershed line. To make sure that the edges are labelled as the object boundaries, the gradient image is rectified by assigning the largest gradient magnitude value to the edge pixels first. The unlabelled pixels are processed in a priority value descending order. ST and QU are used to store the unlabelled pixels. For each priority level, there are two steps. In the first step, only pixels with priority higher than the current processing priority are pro-cessed. These pixels can be divided into two groups. The first group includes pixels with higher priority but not labelled in the previous labelling process, and they are stored in QU. The second includes all the unlabelled pixels with priority. The first group of pixels are processed in advance to the second one. After the first step, if the pixel cannot be labelled, it is stored in ST and processed in an reverse order in the second step. If after the second step, the pixel still cannot be labelled, it will be stored in QU and processed together with the pixels of which the priority is lower than marker-based watershed segmentation result. The labelling operation on pixels outside the markers is dependent upon the number of IDs labelled to the neighbouring pixels of the seed pixel. As same as the process of labelling the pixels within the markers, if two pixels are in the same region, their common neigh-boring pixels should not be edge pixels at the same time. This rule should be obeyed in the counting of the number of the ID; the same ID is counted only once, moreover the neighbouring pixel is not counted if it breaks the rule.

3.4 WATERSHED SEGMENTATION

In order to improve the computing speed of segmentation, in this paper a new algorithm is used. The new algorithm is called defined intuitive watershed algorithm that based on the "immersion" watershed algorithm proposed by Vincent and Soille.

The two algorithms have the same process, including sorting and flooding. To be specific, in the same gradient level, Vincent-Soille algorithm uses a FIFO queue to expand gradually from the inside out of the catchment basin. The new algorithm is to scan each pixel according to spatial relationship (from top left to bottom right), and to determine each pixel to belong to an existing catchment basin or a new one. The fundamental basis of the judgment is whether the pixel has marked adjacent pixels. If it has, it belongs to the catchment basin of its marked adjacent pixels. Otherwise it is to be a new minimum region and assigned a new regional marker. In order to avoid the generation of error minimum regions, two concepts of "error catchment basin" and "combined array" are introduced. Specific steps of segmentation are as follows:

1) Sorting: the new algorithm in the calculation of the sorting position takes the spatial location of pixels into account, so the elements of the sorted array meet a certain spatial relationship. The form of values of sorted array is: (X coordinates, Y coordinates, the gradient value).In this array, the smaller the gradient value is, the more forward the position will be. If the gradient value is the same, the pixel in the upper left (of spatial position) is in front.

2) Flooding: for each current scanned pixels, check its 4 adjacent pixels (or 8 adjacent pixels).if one of the 349 adjacent has not yet been marked, then turn to the next adjacent. If the entire adjacent are not marked, a new catchment basin is found and given a new marker. If one of the adjacent has been marked and the current pixel is not yet, then assign the marker of the adjacent to the current. If one of the adjacent and the current are marked, it may find an error minimum region or a watershed ridge lines.

3.5 WATERSHED CONTAINERS

According to implementation of the watershed segmentation algorithm, water is made from the process of spreading each storage pelvic gradually, namely the marked regional internal gradually to the edge of the area adhesions recursive. If the regional in image containers is too finely, which the whole image will be partitioned an infinite number of adhesion areas, if each containers correspond corn grain, it can guarantee the smooth implement impoundment process in grain internal. Therefore build excellent containers and water-shed, will directly determine the adhesion of particle swarm segmentation quality and efficiency. Through the edge detection has won the ideal watershed border, it should also ensure that the pelvic area between each grain to separate and divide boundary adhesion, and with low value area for the entire area.

1) Implementation taking binary processing after purification grayscale image in adaptive threshold;

2) Adapting radius of 10 pixels by type of structure elements, disk, operating binary image corrosion;

3) Taking negative after marking corrosion image, while assure background region pixels for "0" still, corrosion area of pixels is negative;

4) It will take the normalized image edge detection and buy negative corrosion images obtained by, and take "0" as a background, based on the negative marker value for storage, with "1" at the image matrix for watershed.

Through the above treatment, which ensure each corn grain image to have separate water, and relatively clear watershed, pelvic value is negative marker value, fantastic value close to "1", other areas are "0". The recursive operation process that from high value low value area regional was labelled by image of each grain, which like pixel gradient are uniformity, does not exist small containers and omit the impoundment of the interference of computation quantity and containers. It could improve the reliability and efficiency of operation, what's more, because each grain is a relatively independent starting point (saucers). Even though the public boundary (adjacent grain watershed) is discontinuous (existing gap), it also can ensure the effective segmentation adhesion areas. But if grain region and background area are linked, water that rising to a certain height from pelvic will inflow the background. Now water district have not reached threshold. It will mistake the background region as part of the grain area. The original image background region is "0" (black), via the single grain area, only after influenced by impoundment computing, in central small area isn't effected by leak influence, other areas are marked the not "0" value (white). According to the type of (1) method to implement the marker images, taking purification processing to leaked background, it can take "0" background region, the marker value of each grain regional remain unchanged.

4 Experimental results

Block size analysis for determining the optimal block size is shown in Figure 3.

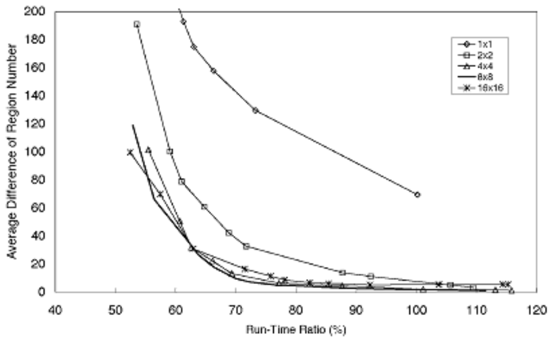

FIGURE 3 Block size analysis showing that 8X8 is the optimal block size.

The accuracy of the segmentation results is evaluated by the difference in region number, that is, the less average difference in region number between the results of the conventional algorithm and the proposed one, the higher the accuracy. Since regions in UAand outside UAare both processed with the conventional watershed algorithm, the positions of watersheds must be very close to those of the conventional algorithm, and only the over-segment problem may occur. The region number information is enough to evaluate the accuracy of watersheds, i.e., the closer the region number is between the result of the conventional watershed transform and that of the proposed one, the more accurate the proposed algorithm is. The ratio of the run time of the proposed algorithm to that of the conventional watershed algorithm is used as another criterion in this analysis. For each block size, a different threshold value is tested to decide the runtime-accuracy curve shown in Figure 3. The lower the threshold, the higher the runtime ratio, and the lower the average difference of region number. The test sequence is Children. Figure 3 shows that 8X8 is the optimal block size because it can provide higher accuracy with less run time than other choices. Several sequences were tested to give a similar conclusion.

The region number corresponding to a different run time is shown in Figure 4.

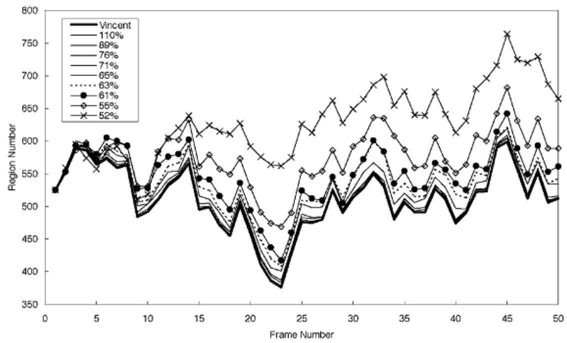

FIGURE 4 Region number of different run-time situations

As can be seen, when the run time increases, the similarity between the results of the conventional watershed and the proposed one also increases. When the run time is reduced to 61%, the region number is still very similar to the reference results. The execution time compared with Vincent and Soille's algorithm. Only core operations of watershed are recorded, namely, the gradient operation, sorting process, and flooding process. Note that the average difference in region number is fixed at 5% in these experiments. The simulation results show that the proposed algorithm can save 20%–50% of the computation. Moreover, the results of the conventional and proposed algorithms are similar. Consequently, the proposed algorithm can reduce computational intensity while maintaining segmentation quality.

5 Conclusions

Aiming at the limitation of watershed segmentation, this paper presents an algorithm of watershed transformation based on opening-closing operation and distance transform. It improves the classical watershed segmentation algorithm based on distance transform, overcoming over-segmentation. The experiment result demonstrates that this method for segmentation inherits the advantage of watershed algorithm based on distance transform that it successfully segment out each dowel in the image bringing convenience to computer vision and auto-counting of dowels. It also overcome over-segmentation existed in traditional watershed segmentation preserving the original edges of each dowel in the image completely.

A new predictive watershed algorithm named Watershed for video segmentation is proposed in this paper. Taking into consideration the temporal coherence property of the video signal, the watershed algorithm can be accelerated. It updates watersheds in changing parts while keeping watersheds in other parts of a frame. The watershed process can be accelerated, and the results are almost the same as those of the conventional watershed algorithms. Moreover, the segmentation results can be further improved with the intra-inter watershed scheme. The proposed algorithm can be combined with any video segmentation algorithm to improve the segmentation results.

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References

[1] Roerdink J B, Meijster A 2001 The Watershed Transform: Definitions, Algorithms and Parallelization Strategies *Fundamental Informaticae* 41 187-228
[2] Vincent L, Soille P 1991 *IEEE Trans Pattern Analysis and Machine Intelligence* **13**(6) 583-98
[3] Meyer F 1994 Topographic Distance and Watershed Lines *Signal Processing* 38 113-25
[4] Meyer F, Beucher S 1990 Morphological Segmentation *Visual Comm. and Image Representation* **1**(1) 21-45
[5] Moga A 1997 Parallel Watershed Algorithms for Image Segmentation *PhD dissertation, Tampere Univ of Technology Finland*
[6] Rambabu C, Rathore T, Chakrabarti I 2003 A New Watershed Algorithm Based on Hill-Climbing Technique for Image Segmenation *Proc. Conf. Convergent Technologies for Asia-Pacific Region, (TENCON '03)* 4 1404-8
[7] Ducourthial B, Merigot A 2002 Parallel Asynchronous Computations for Image Analysis *Proc. IEEE, special session on visual perception: technology and tools* **90**(7) 1218-29
[8] Bertsekas D, Tsitsiklis J N 1997 Parallel and Distributed Computation: Numerical Methods *Athena Scientific*
[9] Chandy K, Misra J 1988 Parallel Program Design: A Foundation *Addison-Wesley*
[10] Renaudin M 2000 Asynchronous Circuits and Systems: A Promising Design Alternative *Microelectronic Eng* **54**(1-2) 133-49
[11] Baudet G M 1978 Asynchronous Iterative Methods for Multiprocessors *ACM* **25**(2) 226-44
[12] Adachi S, Peper F, Lee J 2004 Computation by Asynchronously Updating Cellular Automata *Statistical Physics* **114**(1) 261-89
[13] Merigot A 1997 Associative Nets: A Graph-Based Parallel Computing Model *IEEE Trans Computers* **46**(5) 558-71
[14] Galile B, Renaudin M, Coulon P-Y, Mamalet F 2002 Watershed Parallel Algorithm for Asynchronous Processors Array *Proc ICME IEEE Int'l Conf Multimedia and Expo*
[15] Bieniek A, Moga A 2000 An Efficient Watershed Algorithm Based on Connected Components *Pattern Recognition* **6**(33) 907-16
[16] Bieniek A, Moga A 1998 A Connected Component Approach to the Watershed Segmentation *Math. Morphology and Its Applications to Image and Signal Processing* 12 215-22

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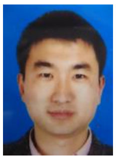

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