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Image Segmentation via Gradient Watershed Hierarchies and Fast Region Merging

[1]*T. Saravanan,* [1]*V. Srinivasan and* [3]*R. Udayakumar*

[1]Deparment of ETC, BharathUniversity,
[3]Department of IT, BharathUniversity, India

Abstract: The watershed algorithm from mathematical morphology has recently become powerful tool for image segmentation. Image analysis has been used successfully in a number of applications to classify different features according to their relative scales. In this paper we present the multistage behavior of gradient watershed regions. Boundaries of gradient watershed regions correspond to the edges of objects in an image. Then an initial partitioning of the image into primitive regions is produced by applying the watershed transform on the image gradient magnitude. This initial segmentation is the input to computationally efficient hierarchical region merging process that produces the final segmentation.

Key words: Image segmentation · Region merging · Watershed transform · Mathematical morphology · Gradient magnitude

INTRODUCTION

Image segmentation plays a very important role in computer vision and image analysis. Many innovative methods have been proposed in the last few decades, but automatic image segmentation for general applications still remains to be an open problem. Recently watershed segmentation [1-3] became a popular tool for different applications. The gradient image is often used in the watershed transformation, because the main criterion of the segmentation is the homogeneity of the grey values of the objects present in the image. Mathematical morphology provides a powerful set of nonlinear image analysis tools which can be applied in a wide variety of situations [4, 6]. For example, images can be segmented into visually sensible regions by finding the watershed regions in a gradient magnitude image [7, 8]. Over segmentation is a well known difficulty with this approach, which has led to a number of approaches for merging watershed regions to obtain larger regions corresponding to objects of interest [9, 10]. The development of morphological scale space operations has also made it possible to study the multiscale behavior of watershed regions.

Definition of the Watershed Transform: Watersheds are one of the classics in the field of topography. Several definitions of the watershed transform have been promulgated: we are going to focus on the once based on the topographical distance when applied to discrete images. For this purpose we need first to introduce two important definitions.

Let f be a digital grey value image of arbitrary dimensionality, which we assume to be lower complete, i.e. it has no plateaus out side the minima. The behaviour of the methods at the plateaus will be explained later. The lower slope of the f at a pixel p, LS (p) is defined

$$LS_{(P)} = \max_{q \,\square\, \square_{G(p)} \,\square\, p} (f(p) - f(q) / d(p,q))$$

where $\square_{G(p)}$ is the set of neighbors of p on the grid G and d(p,q) is the Euclidean distance between pixels p and q. Note that the term inside the brackets is an approximation to the directed gradient to the pixel p. We define 0/0=0 so that, for p=q, this term is zero. In this way, we keep LS (p) □ □□ even when p is a local minimum. The lower slope is necessary to define a steepest slope relation between voxels, which will be used to calculate the watershed transform.

Corresponding Author: T. Saravanan, Department of ETC, Bharath University, Chennai, India.

The concept of lower neighbors is derived directly from the lower slope: for each image pixel p, its set of lower neighbors, denoted as t (p), is

$$
\begin{aligned}
T(p) &= \{p_{\square}\, N(p) \,\square\, f(p) - f(p)/\, d(p, p) \\
&= \max p_{\square} \,\square_{G(p)} \\
&= LS(p)\}
\end{aligned}
$$

So the set of lower neighbours is the subset of neighbouring pixels for which the directed gradient to the pixel p equals its lower slope. If we consider only a first order neighbourhood (all distances are equal). The mapping T (p) introduces a new relation between pixels, which will be used for the watershed transform calculation.

Watershed Hierarchies: Early watershed algorithms were developed to process digital elevation models and were based on local neighborhood operations on squregrids [11, 12]. Improved gradient following methods were subsequently devised to overcome problems with intensity plateaus and squregrids. Other approaches use immersion simulations to identify watershed regions by flooding the image with water starting at intensity minima [13, 14]. Here a variety of data structures including priority ordered queues and hierarchical queues are used to efficiency select pixels to add to watershed regions.

The level of activity in the area of watershed identification reflects to some degree the difficulty of this task. Much of the complexity of current techniques is indirectly due to pixel quantization. For example, if a 5 x 5 region of uniform intensity appears in the image, central pixels will have a gradient zero. In order to determine if this region corresponds to a local maxima or minima or is part of a hillside in the image, all of the neighbors of the flat region must be examined. We avoid this complexity by working with gauss ion smoothed floating point images. This removes all regions with uniform intensity. We can then use fast and simple gradient following algorithms based on local pixel properties to identify watershed regions. Watersheds are traditionally defined in terms of the drainage patterns of rainfall. Regions of terrain that drain drain to the same point are defined to be part of the same watershed. The same analysis can be applied to images by viewing intensity as height. In this case, the image gradient is used to predict the direction of drainage in an image. By following the image gradient downhill from each point in the image, the set of points which drain to each local intensity minimum can be identified. These disjoint regions are called the watersheds of the image. Similarly, the gradients can be followed uphill to local intensity maximum in the image, defining the inverse watersheds of the image.

Flow Chart of Proposed Methodology: The proposed methodology is a two stage process. The first process uses gradient computation to produce a primary segmentation of the input image, while the second process applies the improved watershed segmentation algorithm to the primary segmentation to obtain the final output.

Improved Watershed Segmentation Algorithm: The gradient magnitude of the primary segmentation is obtained by applying the Sobel operator. The Sobel filter has the advantage of providing both a differencing and a smoothing effect. Unlike the conventional watershed algorithm, we perform thresholding technique in [15, 16, 17], which is based on the histogram of the normalized gradient magnitude. All edge map pixels with values greater than the threshold retains their original values, while those edge map pixels with values less than the thresholdhad their values set to zero [18-22]. The rainfall simulation is then applied on the improved edge map.

80	73	71	79	82	80
74	69	66	68	71	73
68	67	65	67	69	71
74	70	66	68	62	67
79	71	68	63	61	66
82	80	70	66	64	68

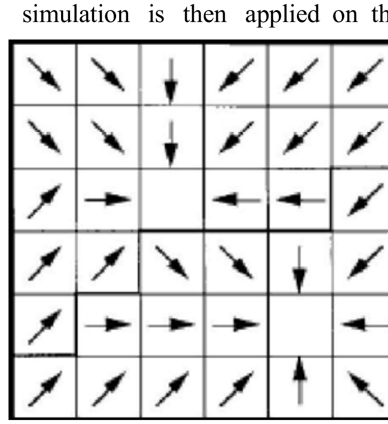

Fig. 1: Simple example of watershed regions and their boundaries. The watershed boundary is shown in bold.

The steepest decent of rainfall is implemented by using a 3 x 3 window centered on each pixel of the gradient map. We compute the steepest gradient direction from its 4 - connectivity neighboring pixels. The neighboring pixel along with steepest direction is marked and the window shifted along that direction. The process of marking pixels shifting window is repeated until the path reaches a minimum. The pixels constituting the path adopt the label of that minimum. Repeat the rainfall simulation by tracing a path of steepest decent for all pixels that are unlabelled. The paths reaching a common minimum adopt the paths reaching a common minimum and constitute a catchment basin, which refers to a partitions constitute the initial segmentation map. The initial segmentation map is heavily over segmented. Hence we implement a post - segmentation merging process in our watershed algorithm. This is unlike the conventional algorithm. The objective of the post - segmentation merging step, which is based on spatial criteria, is to reduce the number of partitions significantly without affecting the accuracy of the segmentation map.

RESULTS AND CONCLUSION

This methodology which incorporates the gradient computation with the improved watershed algorithm has been proposed. It overcomes the drawbacks of the over-segmentation and sensitivity to noise of the conventional watershed transform.

The experimental results have shown that our proposed process of using gradient computation to obtain primary segmentation of cameraman and Baboon are shown in Fig.3 and Fig.4. By applying improved watershed algorithm we obtain the segmentation map

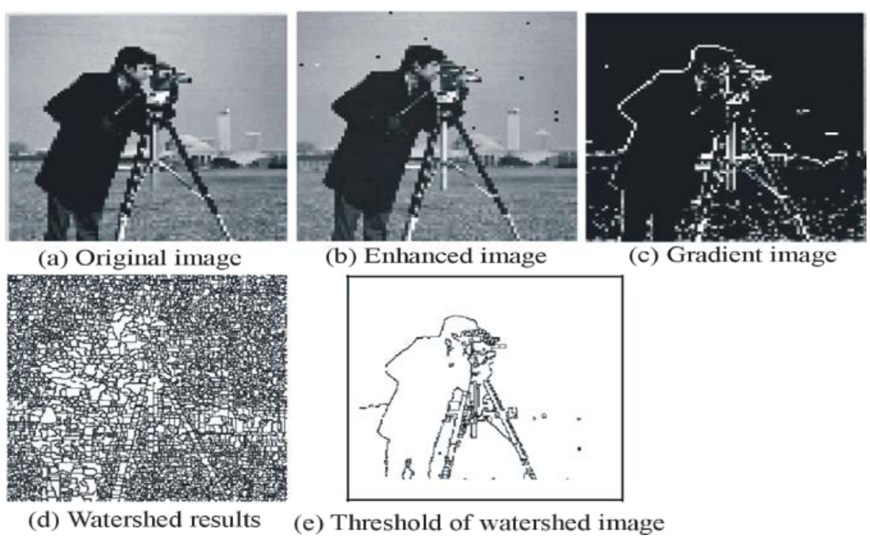

Fig. 3: Cameraman:

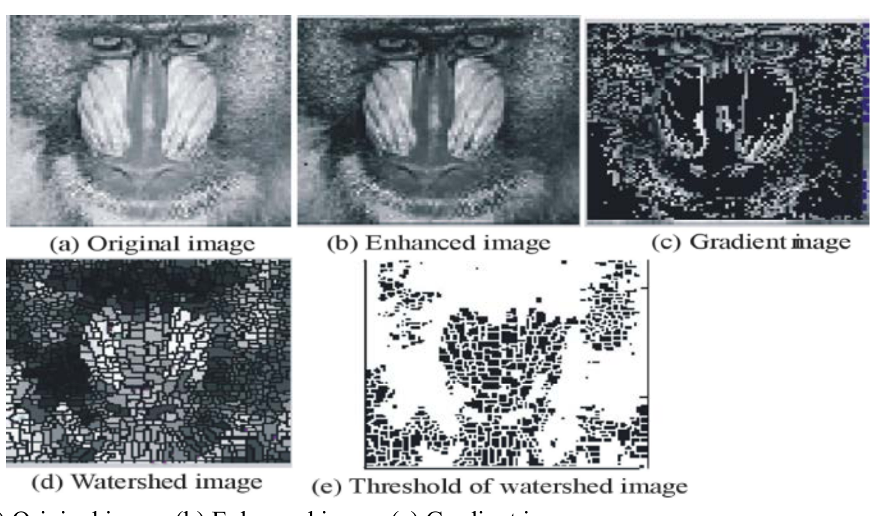

Fig 4: Baboon: (a) Original image (b) Enhanced image (c) Gradient image

which is more representative of the various features of the given input image and the image is thresholded using hierarchical threshold the the region of interest can also be segmented from the image. Hence the net area can be calculated to estimate its size.

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