SEGMENTATION OF TOOTH USING WATERSHED TRANSFORM AND REGION MERGING

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ABSTRACT

Due to the great influence in image analysis and processing systems, the problem of image segmentation has been studied for years; there is not yet any automatic method able to correctly process any kind of image. In this study we did concentrate about the most important method of segmentation, “The Watershed transformation”. However, The watershed method has interesting properties that make it useful for many different image segmentation applications: it is simple and intuitive can be parallelized, and always produces a complete division of the image, when applied to medical image analysis, it has important drawbacks: over segmentation, sensitivity to noise, poor detection of thin or low signal to noise ratio structure and others problems, the current approach we use due to correct some drawbacks, to minimized the number of watersheds by merging it but is still close to the original.

Keywords: *Image, Watershed Transform, Segmentation, Merging Region, Cost, Variance, Nodes, Region*

1 INTRODUCTION

Automatic image interpretation becomes more and more important. Increasing the resolution of the different acquisition tools generates a mass of data that can no longer be processed manually. In this context, automatic methods must make it possible to analyze an image in order to help the human expert in his interpretation work [1]. Among these, segmentation, this aims to extract from images a set of information or relevant regions, which the regions satisfy some specified criteria. A commonly used criterion is that of homogeneity, the region should be homogeneous with a respect to some properties, such as color, texture, forms or others. The proposed algorithm in this paper belongs to the category of the hybrid segmentation techniques since it results from the integration of graph and region based techniques through the morphological watershed transform. Firstly, a filter gradient is implemented to detect the boundary of the objects in the input gray-scale image and we mark the minimum gray value of pixels before adopting watershed transformation .Then each region is represented by a graph of node and the neighboring nodes are saved in a matrix for the computation of region dissimilarity between the adjacent nodes according to three features: intensity mean, intensity variance and the number of pixels in a region. Last, the two regions which have minimum cost are merged, the cost among the merging nodes and their neighboring nodes and the labels of the regions are updated. This will be iterated until the final segmentation result [2]. The experimental result shows that the algorithm proposed is more efficient and has a reasonable segmentation [3].

This paper is separated in 2 sections: first, the presentation of watershed transform and application on medical tooth image with a registration of information and two, the approach of region computing and merging algorithm.

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2 WATERSHED SEGMENTATION METHOD

2.1 Watershed transformation

In geography, a watershed is the ridge that divides areas drained by different river systems. A catchment basin is the geographical area draining into a river or reservoir [4]. The watershed transform is the most using method in mathematical morphology The intuitive description of this transform is quite simple: if we consider the image as a topographic relief, where the height of each point is directly related to its gray level, and consider rain gradually falling on the terrain, then the watersheds are the lines that separate the catchment basins. Generally, the watershed transform is computed on the gradient of the original image, so that the catchment basin boundaries are located at high gradient points [5].
To get the watershed image transformation:

- Associate each pixel value with an altiutude
- Imagine the immersion of a relief in the water
- Water can only enter the valleys by its minima
- The watershed is presented by the points where two disjoint lakes meet during the immersion

To use watershed segmentation we must start by a gradient filter

2.2 The gradient filter for edge detection

The watershed transformation produces excessive over-segmentation as one of its drawbacks. Therefore some form of preprocessing is required to produce a segmentation that better reflects the arrangement of objects within the image. So we compute the gradient magnitude of the image which has high pixel values along object edges, and low pixel values everywhere else. To obtain the gradient of an image requires computing the partial derivatives $\frac{\partial f(x,y,z)}{\partial x}$ and $\frac{\partial f(x,y,z)}{\partial y}$ and $\frac{\partial f(x,y,z)}{\partial z}$ at every pixel location in the image and a digital approximation of the partial derivatives over a neighborhood about a point is required [6].

$$G_x = \frac{\partial f(x,y,z)}{\partial x} = f(x+1\,,y,z) + f(x,y,z)$$

$$G_y = \frac{\partial f(x,y,z)}{\partial y} = f(x,y+1\,,z) + f(x,y,z)$$

$$G_z = \frac{\partial f(x,y,z)}{\partial z} = f(x,y,z+1) + f(x,y,z)$$

Here, the mask we use is called the Sobel liner filter. The Sobel filter can detect edge strength and direction and has a better noise-suppression we called the smoothing characteristic which is an important issue when dealing with derivatives [5].
The SOBEL filter is :

$$S = (G_x^2 + G_y^2 + G_z^2)^{1/2}$$

Similarly, the gradient filtering for gray images can make the result after watershed transform more reasonable.

2.3 Detection of the Regional Minimum

After using the gradient filter, the marker-controlled method is employed to reduce the number of regions. First we compute the locations of all regional minima in an image, and eliminate these extraneous minima with the function which computes the set of "low spots" in the image that are the set of height threshold h than their immediate surroundings [7]. The regional Minimum M of a grayscale image D is a connected component of pixels with a given value h, such that every pixel in the neighborhood of M has a strictly higher value. We define J and I be two grayscale images defined on the same domain D, taking their values in the discrete set{0, 1, 2…N-1} and $J \geq I$, for each pixel $p \in D$, which means the intensity value of each pixel in J is greater or equal than pixel in I. The elementary geodesic erosion is: $\varepsilon_i^1(J) = (J\theta B) \vee I$ where $\vee$ stands for the point wise maximum and JθB is the erosion of J by fat structuring element B. The grayscale reconstruction $P_I(J)$ of the mask I from the marker J. is obtained by iterating grayscale geodesic erosions of J "above" I until stability is reached [8].
We can defined the minima K(I) for an image I by : K(I) = Pi(I + h) - I they Geometrically a connected component of pixels such that every pixel p neighbor of D satisfies two conditions :

- $I(p) < \min \{ I(q) / q \in D \}$
- $\max \{ I(q) / q \in D \} - \min \{ I(q) / q \in D \} < h$

According to the algorithm, we can obtain minima which are higher than the lowest spot in their surroundings.

2.4 The Watershed transformation algorithm

We present the current algorithm of watershed transform after a gradient filter

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The Imput: image I[M,N,L], real E no altitude
The Output: Table of integers T[M,N,L]
MIN, MAX : the minimum and the maximum of I
F : the FIFO queue and n : altitude pixels
(the pixels are first sorted in ascending order of altitude)
(any image minima has a different label)

Begin
For h From MIN to MAX
- we select the pixel of the level [h, h + E]
- We add the selected pixels in the pool to the F
For each pixel P of the F
- we see the 4 adjacent pixels of P and put label in the box that corresponds to P in T
- all pixels that are adjacent to P + 1 and selected are added at the end F
we propagate the labels of the basins to the pixels that are marked as neighbors

END For,
End For,
END

After using the watershed transform to our image we conclude (figure 1) :
The advantages:
- high precision on the boundaries obtained
- perfect distinction of two glued regions

The inconvenient :
- over – segmentation
- sensitivity to noise

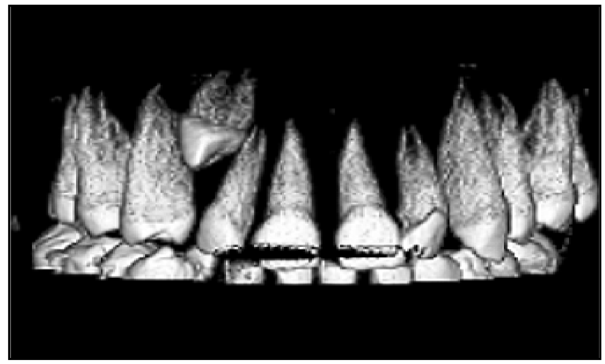
To solve this inconvenient we must merging the regions obtained after using watershed method

2.5 The Region Merging method

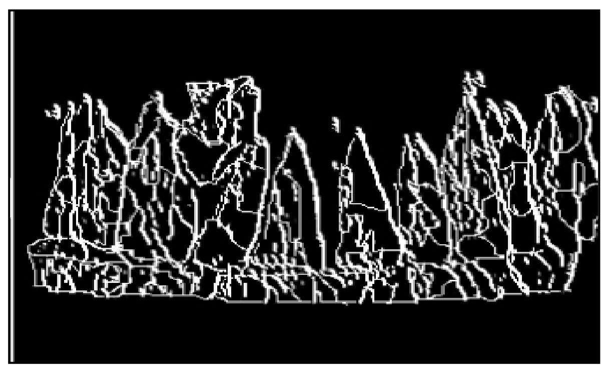
After watershed transform, the image is substituted to a set of regions adjacency, each region can be represented as a node and an edge connecting two nodes are inserted if two regions are adjacent [9]. The definition of the data structure can be noted as: M (V, E, W) where : V denotes the set of regions called also nodes, E the set of edges between the adjacent nodes and W the sets of adjacent region dissimilarity, the cost. We present V, E and W by matrices while V records three features of each node: the number of pixels, the mean, and the variance, E records the adjacent nodes of each node and W records the cost between each node and its neighbor nodes. The structure in W is corresponding to the structure in E [10].

3 ALGORITHM AND RESULTS

Based on the structure, we're going to divide the algorithm on two stages. In stage 1, we computed three features of each node; we get adjacent nodes of each node and calculate the cost between them [11]. In stage 2, we merging every two adjacent regions whose cost is minimum which denotes the two regions are the most similar. The process will iterate until the image is composed of a certain number of regions [12].



a



b

Figure 1: A - Initial Image B – Watershed Transform After Gradient Filter

3.1 Algorithm description:

3.1.1 Region cost calculation

The input: the watershed image. Each region is labeled by an only number from 1 to N, and the edges segment the regions are labeled by 0.
- Matrix V denotes the set of regions whose mean, variance and the amount pixels of each node are recorded in V. The mean feature that is the mean gray value of pixels in a node is employed to distinguish the gray-scale image intensity of regions, and variance is a measure

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of the amount of pixels' gray value variation and deviation in a region, also variance is closely related to the variation of texture.

- During the step, the adjacent nodes of each node are expressed by $E_{i,j}$ with $I,j = \{1,2,\ldots,n\}$ / $I \neq j$ For a region
- The region similarity (region cost) is calculated between adjacent nodes. VA_1 denotes the number of pixels in region a, VA_2 denotes mean value of gray value in region a, and VA_3 denotes the variance of gray value in region a. Hypothesis VB is an adjacent node of VA, thereby $E_{i,j} \in E$ and $W_{i,j} \in W$. Then the difference of mean and variance between VA and VB is : $D = | VA_2 - VB_2 |$ and $D' = | VA_3 - VB_3 |$

3.1.2 Region Merging:

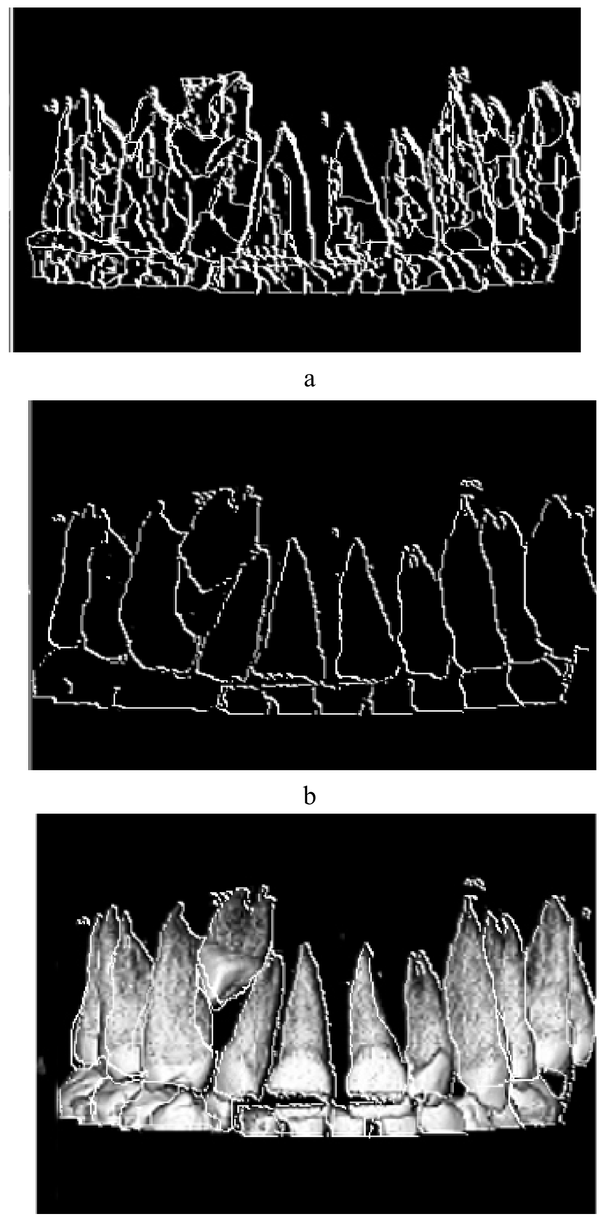
The input: Image G after region cost calculation. $G = \{V, E, W\}$.

- Calculate the number of regions, than output the partitioned image
- Find the minimal $W_{i,j} \in W$, set $tmin = \min\{i, j\}$, and $tmax = \max\{i, j\}$.
- The node tmax is merged into node tmin, while pixels in region tmax or pixels of watershed between regions tmax and tmin are labeled tmin. The rest of pixels labels are not altered.
- Calculate the three features in region tmin over again,
- update the information of Vtmin and delete Vtmax.
- The updated neighboring nodes of tmin is : $Etmin = Etmin_i + Etmin_j$
- Re-calculate the nodes adjacent to tmin or tmax and the cost between them

Finally, we obtain a new segmented image and the procedure will continue from the first step to the last step when adjacent regions merge once until we get required amount of regions [13].

3.2 Results and discussion:

In the program, there are two steps which are important. One is searching about a segmentation of teeth using the watershed transformation to calculate the number of segmented regions S. Firstly; we filter the original image to remove all non-significant minima: this is the filtering approach. Second we choose the number of local minima and therefore the number of areas that we want to highlight with the LPE: it is the approach markers (swamping). Finally a first LPE can serve as a marker for a second, and the area it delimits gives rise to a mosaic image. This image is no longer built by pixels, but as a planar graph (figure1). After segmentation we notice an over-segmentation there are about 112 regions, to minimize the number of regions we turn to the second steps, it's to merging this region.



a

b

Figure 2: A – Watershed Segmentation With 112 Regions, B – Watershed Segmentation And Merging Regions, C- Final Segmentation On Real Image

As the intended application of the segmentation scheme is in region extraction for content-based retrieval, the image is partitioned into a certain number of regions. Applied to our problem the tooth image showed in figure 1, the result image (figure 2) present the number of region decrease from 112 regions to 60 regions to finally 30 regions However, our method has some defects on segmenting the texture images due to we set greater weight on the coefficient of mean gray intensity value than the variance of gray value in a region. When the difference of gray value in an image is little, the segmentation work by our algorithm is very difficult (figure 2 – c) [14].

4 CONCLUSION:

The segmentation of an image by watershed method is a powerful tool for analyzing the topography of an image. It has several immersion implementations "Vincent and Soielle, 1991" and geodetic distance "Myer, 1988" [15][16].
In this paper, we propose a novel image segmentation approach based on watershed transformation and region merging. We improve the watershed transform by preprocessing techniques, and use region number, mean and variance features to calculate cost during merging algorithm after watershed transform.
Finally after partitioned the image into a certain number of regions we minimize the number of regions. Our algorithm is implemented for several grayscale images, and in most cases the results are very satisfactory both with respect to segmentation performance and execution times, and also we don't neglecting a margin of error that differs from one image to another.
The merger process we have adopted allows to obtain a final segmentation of the image on the basis of the depth of the watershed [17]. The results obtained show the success and effectiveness of the proposed approach for image segmentation. In effect the method offers good results; it helps to detect the different parts in the picture.

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