On Points Geometry for Fast Digital Image Segmentation

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Abstract

Automatic segmentation of digital images is of utmost importance in many applications especially those related to machine vision, i.e., robotics and vision in the production industry. There exist different algorithms to carry out image segmentation. This paper presents a novel image segmentation algorithm with low computational complexity. The proposed approach is based on Delaunay triangulation (DT) which is the dual of Voronoi Diagram (VD), a well-known technique in computational geometry. VD is presently implemented in many areas, but researchers primarily focus on its use in skeletonization and in generating Euclidean distances. DT Triangles form a mesh from any input dot patterns which are in our case the image intensity colours. The union of all triangles is called the convex hull which helps generate clusters of intensity values using information from the vertices of its external boundary. In this way, it is possible to produce segmented image regions. We used the BioID face database to test our algorithm as we aim to produce an adaptive Steganography system which uses an object oriented approach.

1. Introduction

Automatic segmentation of digital images is of utmost importance in many applications especially those related to machine vision, i.e., robotics and vision in the production industry. Image segmentation is also an important factor in medical imaging systems. Even though various methods have been introduced, almost all of them act on image data (intensity or colour values) in the 2D world. This fact tends to make these algorithms complex and computationally expensive. In this work we provide a real time method for image segmentation based on points (maximum of 255 points only). Researchers act on the 2D level and we found that a very good approximation of image segmentation can be simply derived from the histogram of the examined image. Hence, our proposed algorithm is simple yet powerful. Therefore, we can assert that the image segmentation problem can be solved by means of the points' geometric relationship at the level of 1D data, i.e., the standard histogram.

This work facilitates our ongoing project which targets Steganography (the science of concealing hidden data within digital images). Creating an adaptive Steganography system forms our primary objective. We have successfully developed Steganography methods which use an objects oriented approach in colour images. We focus on detecting and hiding within human skin tone regions. This paper proposes an image segmentation method which will handle grayscale images for our system.

This paper is organised as follows: the next section highlights a brief introduction to image segmentation, section 3 shows our proposal in detail, some results and contrasts our work to the popular K-Means segmentation algorithm and to the automatic gray threshold. We conclude our work in section 4.

2. Review of Image content segmentation

Broadly speaking image segmentation techniques [1] can be classified into two categories: namely boundary-based techniques and region-based techniques.

The K-means algorithm was first introduced by Forgey [2] and MacQueen [3]. It is a clustering method with low computational complexity and that is why we chose to compare our method with it as both methods share this same feature. In k-means clustering, we are given a set of n data points in d-dimensional space R^d and an integer k. The problem is to determine a set of k points in R^d, called centers, so as to minimize the mean squared distance from each data point to its nearest center [4].

It is interesting to note that most segmentation techniques involving gray scale images can be extended to colour images. The basic and most traditional method of segmentation is based on dynamic thresholding of the image histogram. The threshold value is determined by examining the minima between two peaks in the histogram. A repetitive thresholding process yields segmented regions. Obviously this method is feasible only when the examined image generates a bi-model histogram. Various threshold points, for the same image, can be obtained by applying this method on different colour spaces resulting from RGB colour transformations. Region-based algorithms include region growing, region splitting and region merging. Each of these methods triggers a seed to analyze the pixel values. The region growing method starts with a pixel seed and then examines the neighbour pixels to determine any homogeneity in terms of brightness. The selection of the seed and the order of the scanning process are crucial to its performance. In the region splitting method, the whole image is taken as the initial fired seed. This image is then split into four blocks covering homogeneous areas. Again these four blocks are considered as the new seeds and the operation is repeated until homogeneous regions are found. In this algorithm, the final segmentation tends to retain the shape of the data structure of the splitting mechanism. Region merging can be any one of the former two, but the difference is that homogeneous regions are merged during the process. The nearest neighbour algorithm to K-means is a machine-learning algorithm that implicates voting by a pixel's neighbours for homogeneity. Edge detection is another means of image content segmentation. Different operators for this have been introduced, including Sobel, Prewitt, Laplacian, and Canny. All such methods share the goal of targeting abrupt changes in image intensities, but differ in the weights assigned to each value in the mask.

Suhail et al. [5] presented a practical implementation of the Voronoi Diagram (VD) to segment images based on selected feature points. These points are exclusively identified and selected after careful analysis of unique pixels residing along the image edges of high gradient magnitude. For experimentation, all pixels with a gradient magnitude larger than 75% were chosen. This process was followed by a normalized cross-correlation in which each window was cantered with one of the selected points. If any window survived the matching, meaning that it did not have another intensity similar window, its point would be selected as a unique feature point. The authors claimed their proposal could be used in recovering distorted images and also in watermarking.

Burge and Burger [6], in an attempt to produce a new class of automatic passive biometrics, suggested the ear as the basis for a supplementary source of evidence in identification and recognition systems. Development of their ear biometric graph model proceeded through different stages. First, a deformable contour method was used to locate the ear area. This process was followed by applying a canny edge detector. For selective curve extraction, the edge relaxation method was applied, and only curves with a length greater than 10 pixels were retained. A generalized Voronoi diagram was initiated to yield a neighbour graph that uniquely identified the studied ear.

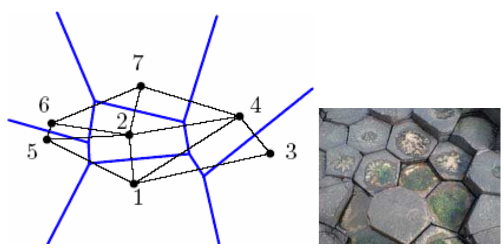
3. Image segmentation using Voronoi Tessellations

Applications of image segmentation can be found in a wide variety of areas such as remote sensing, vehicle and robot navigation, medical imaging, surveillance, target identification and tracking, scene analysis, product inspection/quality control, etc. Image segmentation remains a long-standing problem in computer vision and has been found difficult and challenging for two main reasons [7]: Firstly, the fundamental complexity of modelling a vast amount of visual data that appears in the image is a considerable challenge; the second challenge is the intrinsic ambiguity in image perception, especially when it concerns so-called unsupervised segmentation (e.g., a decision whereby a region cut is not a trivial task).

Our approach is based ultimately on the Voronoi Diagram (VD), which employs a versatile geometric structure [8; 9; 10]. VD has contributed to various research problems such as the travelling salesman problem, a problem which was treated in the 1800s by the Irish mathematician Sir William Rowan Hamilton and by the British mathematician Thomas Kirkman[1]. Despite its usefulness in various fields ranging from remote sensing to robot navigation, this method was largely forgotten in applications in image segmentation until Burge and Burger [6] rekindled interest in it. The approach was based on extracting feature points which were then used to define the centres of the Voronoi cells' for image segmentation. Although our method is similar in that it uses VD, our methodology and image targets are completely different.

Concise definitions of VD and DT are presented. Given a set of 2D points, the Voronoi region for a point P_i is defined as the set of all the points that are closer to P_i than to any other points. More formally we can say: Let $S = \{P_1, P_2, \ldots P_n\}$ be a finite subset of R^m and let $d: R^m \times R^m \rightarrow R$ be a metric. We define the Voronoi region VR (P_i) of a point P_i via VR $(P_i) = \{P \in R^m \mid d(P, P_i) \leq d(P, P_j)$ for all $j = 1, 2, \ldots, n, j \neq i\}$, i.e., VR (P_i) is the set of all points that are at least as close to Pi as to any other point of S. The set of all n VR is called the Voronoi Diagram VD(S) of S [8].

The properties of Voronoi polygons draw many researchers' attention. As a result, various algorithms have been developed to compute the VD. Among these methods we make special mention of the Divide and Conquer Algorithm, the Region Growing Algorithm [9], Fortune's Algorithm [11], and the Fortune Plane Sweep algorithm [12]. The dual tessellation of VD is known as the Delaunay Triangulation (DT) (as shown in Fig. 1).



(a) (b)

Fig. 1. (a) Delaunay triangulation of seven dot patterns (black) and their VD (thick lines in blue). (b) This naturally created Voronoi Diagrams on these rocks might have been the inspiration behind the discovery of VD.

The duality comes about as follows: vertices in the Voronoi diagram correspond to faces in DT, while Voronoi cells correspond with vertices of DT. Once the VD for a set of points is constructed, it is a simple matter to produce DT by connecting any two sites whose Voronoi polygons share an edge. More specifically: let **P** be a circle free set, i.e., no points residing inside the circle. Three points, *p, q* and *r* of **P** define a Delaunay triangle if there is no further point of **P** in the interior of the circle which is circumscribed to the triangle *p, q, r* and its centre lies on a Voronoi vertex; Fig. 2 depicts this notion.

[1] http://en.wikipedia.org/wiki/Traveling_salesman_problem, accessed on 08-04-2008 at 12:32

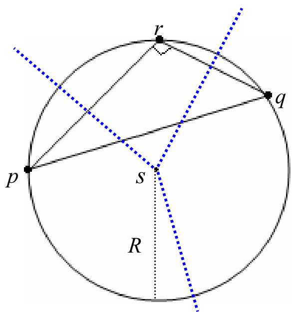


Fig. 2. Delaunay construction. *pqr* defines a Delaunay triangle when the centre (*S*) of the circle circumscribed to *pqr* is a Voronoi vertex.

Various literature studies have tended to apply VD on the image itself (after binarizing it and capturing its edges). This is usually time consuming; therefore, we apply VD not on the images but instead on a few selected points (<=255). Thus, VD is constructed from feature points (generators) that result from gray intensity frequencies, see Fig. 3. This would have a time complexity of $O(n\log(n))$, where n<=255.

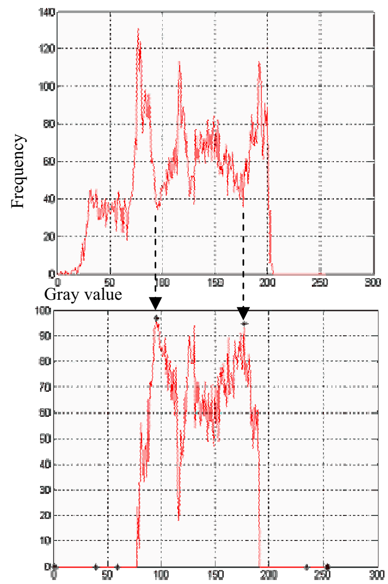


Fig. 3. Top: Gray-level frequency (getting global maxima). Bottom: Exposing local minima.

The proposed technique resembles the dynamic thresholding method used for segmentation, but it differs in terms of divide and merge-decision making. Human faces have a special colour distribution that varies significantly from the background. VD is used to construct Delaunay Triangulations (DT) from points on the image histogram. The outer boundary of DT is simply the Convex Hull (CV) of the set of the feature points, as shown in Fig. 4. Hence, the two global maxima are obtained by extracting the top two values in the DT list of vertices; which correspond to the peaks in the histogram. In order to get the minima that fall between these two peaks, a new set of points are spawned using the following steps:

- Generate the host image histogram
- Generate VD /DT to obtain the list of vertices and get the two peaks
- Set all points below the first peak to zero, and set all points beyond the second peak to zero
- Set all points that are equal to zeros to be equal to the `argmax (peak1, peak2)`

- Derive the new points using:

$$Val_{new}(x) = | (Val(x) - max(Val(x))) |$$

This process will yield a local flip effect on the image histogram. The previous course of action will expose the minima points to be part of the convex hull constructed by DT, as shown earlier in Fig. 3 (Bottom).

These unique feature points are then sorted in ascending order, based on their intensity values, to outline a vector (V) containing values that form the ranges with which merging and splitting decisions are made. The following paradigm is applied:

```
Input: Host gray scale image Ψ
Input: Vector generated by the previously described procedure V
Initialize a new vector d = []
Set all pixels in Ψ smaller than V(1,1) to black (0)
Set all pixels in Ψ greater than V(length(V(:)),1) to black (0)
for i = 1 to length(V(:))−1 do
     if i ==1 then
     set all (Ψ >= V(i) AND Ψ <= V(i+1))
         to V(i+1)
         d= add_to_List [V(i+1), d]
     else
     set all (Ψ > V(i) AND Ψ <= V(i+1))
         to V(i+1)
         d= add_to_List [V(i+1), d]
      end if
end for
Output: Segmented gray scale image Ψ_Segmented
```

Bear in mind that the outer layer of DT contains vertices which are but some of the selected Voronoi (VD) generators, meaning that the vertices forming the CH are what we are interested in. In this case these vertices give a direct access to their respective gray values from the studied image, as shown in Fig. 4.

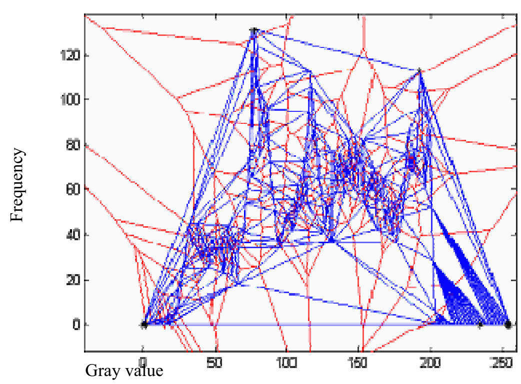


Fig. 4. Delaunay Triangulation generated from points of the histogram shown in Fig. 3.

In summary, our designed system (Complement/Direct Segmentation: DS/CS) can handle segmentation of images with different complexity, as can be seen from the example shown in Fig. 5. Moreover, our algorithm can be extended to RGB images as successive applications of the method on each colour channel separately would result in RGB colour image segmentation.

One of the most efficient segmentation techniques is the so called K-Means clustering. For the purpose of evaluating our proposed method of segmentation, a comparison is carried out. Fig. 6 shows the output of each algorithm. Unlike the K-Means algorithm, our method for segmentation does not need any parameters to be set; rather it is a fully automated and unsupervised process. All it needs in order to function is an image histogram, which is obviously an advantage.

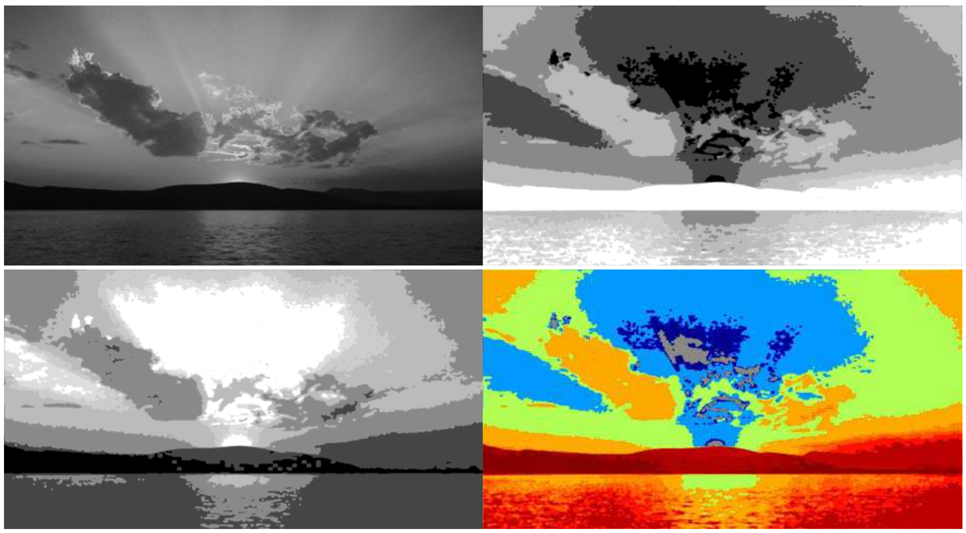


Fig. 5. Application of the algorithm on a scene of nature. Top to bottom and left to right: Original image, direct image segmentation (DS), image complement segmentation (CS) and the corresponding colour mapping of DS.

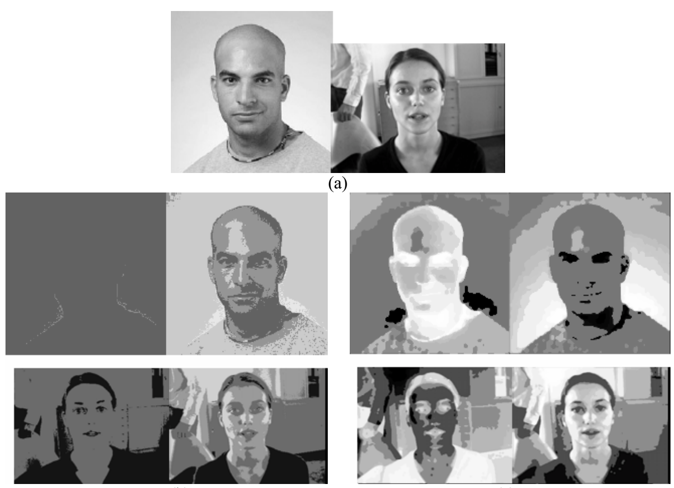


Fig. 6. Comparison of image segmentation using the K-Means and our method (CS). (a) Original images, (b-left) Output of K-Means segmentation with Gauss law and (b-right) output of K-Means segmentation with Rayleigh law. (c-left) The proposed image complement segmentation (CS), and (c-right) direct segmentation (DS).

Automatic image segmentation by means of histogram cut is widely used despite its simplicity and even though it produces a binary image, i.e., two clusters. Fig. 7 shows this method along with our proposed VD segmentation. Further test images are shown in Fig. 8. As can be seen, our method can cope with different images exhibiting complex background and images with uneven illumination. An obvious outcome of image segmentation is detailed representation of a given image with least possible number of colours, see Table 1. Figure 9 shows our algorithm performance on different image sizes.

(a) ;8 (b) ;i] (c)

Fig. 7. Contrast of our method against automatic gray threshold. (a) Original, (b) VD segmentation and (c) Gray threshold segmentation.

Fig. 8. Test results of face segmentation on Set 3 (BioID). (Columns left to right) Original images, Voronoi based image segmentation.

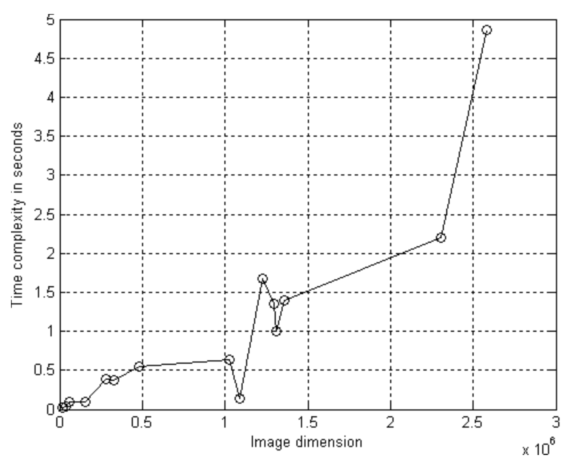


Image dimension	Time complexity
16384 pixel	0.0160 second
35720	0.0310
36864	0.0310
38400	0.0320
57800	0.0940
154400	0.0940
280150	0.3900
327370	0.3750
480000	0.5470
1024000	0.6410
1091500	0.1410
1228800	1.6720
1296000	1.3590
1310700	1.0000
1357100	1.3910
2304000	2.2030
2583600	4.8590

Fig. 9. Time complexity of test images, with different dimensions, using MATLAB (interpreted language).

Table 1. Benefit of Segmentation in Reducing Colour Representation (Re-sampling) of the image of Fig 7

Gray Values in the Host Image	After Segmentation using our Method	
	Direct	Complement
254	20	19

4. Conclusion

We have presented our novel algorithm for image segmentation based on points geometry derived from the image histogram. Our proposal shows less complexity while maintaining high performance. We have compared our approach to that of the well-known K-Means segmentation algorithm. This work is a pre-processing phase for our ongoing research on biometric inspired digital image Steganography [13; 14; 15].

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