ANALYSIS OF IMAGES BY USING EFFECTIVE EWCVT MODEL IN IMAGE SEGMENTATION

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ABSTRACT:

Image Segmentation algorithms generally are based on one of the two basic properties of intensity values: discontinuity and similarity. In the first case, the approach is to partition an image based on abrupt changes in intensity,such as edges in an image. The approaches in the second case are based on partitioning an image in to regions that are similar according to set of predefined criteria. Centroidal Voronai Tessellation (CVT) based methodologies have been proven to be very useful in many diverse applications in science and engineering. CVT-based algorithms reduce to the well-known k–means clustering and are easy to implement. The development of CVT methodologies leads to an *edge-weighted centroidal Voronoi tessellation* (EWCVT) model for image segmentation and propose some efficient algorithms for its construction. Our EWCVT model can overcome some deficiencies possessed by the basic CVT model; in particular, the new model appropriately combines the image intensity information together with the length of cluster boundaries, and can handle very sophisticated situations. We demonstrate through the use of Matlab tools, the efficiency, effectiveness, robustness, and flexibility of the proposed method.

Keywords: Image processing, Image segmentation, edge detection, CVT(Centroidal Voronai Tesselation)

I. INTRODUCTION

PEOPLE have benefited a lot from technological advances in communications, entertainment, medicine, mapping, and manufacturing, which are often brought by the development of image processing techniques. Typical image processing includes image enhancement, restoration, compression and segmentation. These techniques are widely used in computer vision, feature detection, medical image processing, morphological image processing, remote sensing, and so on. To further develop these techniques and apply them in more sophisticated situations, we first need a better understanding of images. Clustering is one of the very powerful tools for retrieving generic structural information from a large set of data. Roughly speaking, clustering classifies a large data set into smaller data groups, such that the data in each cluster share some similarities, which can be specified according to different applications. In the context of image processing, the data sets take the form of images.

The model of centroidal Voronoi tessellations (CVTs)has been introduced to numerous fields and applications such as image processing, data analysis, computational geometry, sensor network, numerical partial differential equations, cellular biology, statistics, and the territorial behavior of animals. In its simplest form, CVT-based algorithms reduce to the well-known K-means clustering technique. When applying the CVT model to image segmentation problems, the partition of a data set actually becomes an optimization process of choosing *generators* with respect to a special *energy*. Much of the effectiveness of CVT-based algorithms originates from this feature in image segmentation and other image processing applications. Moreover, CVT provides a general framework for the energy minimization process and allows convenient improvements, substantial generalizations of existing clustering strategies. The central task of image segmentation is to partition an image into subsets so that the elements of each subset share similar attributes and properties. Once the partition is determined, we can easily identify the boundaries or edges which separate the clusters. In the past few years, there have been many methods developed for image segmentation, Some of popular and successful techniques include the level-set method which is typically a partial differential equation based variational method and spectral clustering algorithm which is an eigenvector based method. More recently, graph-based algorithms have attracted a lot of attentions as a highly efficient and effective approach of partitioning the image into a small number of homogeneous regions

In this paper, we use the improved basic CVT-based clustering Method and developed new *edge-weighted centroidal Voronoi tessellation* (EWCVT) model and corresponding EWCVT-based algorithms for Edge segmentation. In this section, we will discuss the selection of parameters in our EWCVT model for edge deduction and present results obtained by applying our EWCVT-based deduction algorithms to various synthetic and real images from different modalities. The Synthetic and real images are experimentally checked up using Mat lab tool.

II. EDGE DETECTION CONCEPT

Edge detection is a terminology in image processing and computer vision, particularly in the areas of feature deduction and feature extraction, to refer to algorithms which aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities.

Motivations

The purpose of detecting sharp changes in image brightness is to capture important events and changes in properties of the world. It can be shown that under rather general assumptions for an image formation model, discontinuities in image brightness are likely to correspond to:

- discontinuities in depth,
- discontinuities in surface orientation,
- changes in material properties and
- variations in scene illumination.

In the ideal case, the result of applying an edge detector to an image may lead to a set of connected curves that indicate the boundaries of objects, the boundaries of surface markings as well curves that correspond to discontinuities in surface orientation. Thus, applying an edge detector to an image may significantly reduce the amount of data to be processed and may therefore filter out information that may be regarded as less relevant, while preserving the important structural properties of an image. If the edge detection step is successful, the subsequent task of interpreting the information contents in the original image may therefore be substantially simplified. Unfortunately, however, it is not always possible to obtain such ideal edges from real life images of moderate complexity. Edges extracted from non-trivial images are often hampered by *fragmentation*, meaning that the edge curves are not connected, missing edge segments as well as *false edges* not corresponding to interesting phenomena in the image – thus complicating the subsequent task of interpreting the image data.

Edge properties

The edges extracted from a two-dimensional image of a three-dimensional scene can be classified as either viewpoint dependent or viewpoint independent. A *viewpoint independent edge* typically reflects inherent properties of the three-dimensional objects, such as surface markings and surface shape. A *viewpoint dependent edge* may change as the viewpoint changes, and typically reflects the geometry of the scene, such as objects occluding one another.

A typical edge might for instance be the border between a block of red color and a block of yellow. In contrast a line (as can be extracted by a ridge detector) can be a small number of pixels of a different color on an otherwise unchanging background. For a line, there may therefore usually be one edge on each side of the line.

Edges play quite an important role in many applications of image processing, in particular for machine vision systems that analyze scenes of man-made objects under controlled illumination conditions. During recent years, however, substantial (and successful) research has also been made on computer vision methods that do not explicitly rely on edge detection as a pre-processing step.

A simple edge model

Although certain literature has considered the detection of ideal step edges, the edges obtained from natural images are usually not at all ideal step edges. Instead they are normally affected by one or several of the following effects:

- focal blur caused by a finite depth of field and finite point spread function.
- Penumbral blur caused by shadows created by light sources of non-zero radius.
- Shading at a smooth object edge.
- local specularities or interreflections in the vicinity of object edges.

Although the following model does not capture the full variability of real-life edges, the error function erf has been used by a number of researchers as the simplest extension of the ideal step edge model for modeling the effects of edge blur in practical applications

Edge detection methods

There are many methods for edge detection, but most of them can be grouped into two categories, search-based and zero-crossing based. The search-based methods detect edges by first computing a measure of edge strength, usually a first-order derivative expression such as the gradient magnitude, and then searching for local directional maxima of the gradient magnitude using a computed estimate of the local orientation of the edge, usually the gradient direction. The zero-crossing based methods search for zero crossings in a second-order derivative expression computed from the image in order to find edges, usually the zero-crossings of the laplacian or the zero-crossings of a non-linear differential expression, as will be described in the section on differential edge detection following below. As a pre-processing step to edge detection, a smoothing stage, typically Gaussian smoothing, is almost always applied.

The edge detection methods that have been published mainly differ in the types of smoothing filters that are applied and the way the measures of edge strength are computed. As many edge detection methods rely on the computation of image gradients, they also differ in the types of filters used for computing gradient estimates in the x- and y-directions.

Thresholding and linking

Once we have computed a measure of edge strength (typically the gradient magnitude), the next stage is to apply a threshold, to decide whether edges are present or not at an image point. The lower the threshold, the more edges will be detected, and the result will be increasingly susceptible to noise, and also to picking out irrelevant features from the image. Conversely a high threshold may miss subtle edges, or result in fragmented edges.

If the edge thresholding is applied to just the gradient magnitude image, the resulting edges will in general be thick and some type of edge thinning post-processing is necessary. For edges detected with non-maximum suppression however, the edge curves are thin by definition and the edge pixels can be linked into edge polygon by an edge linking (edge tracking) procedure. On a discrete grid, the non-maximum suppression stage can be implemented by estimating the gradient direction using first-order derivatives, then rounding off the gradient direction to multiples of 45 degrees, and finally comparing the values of the gradient magnitude in the estimated gradient direction.

A commonly used approach to handle the problem of appropriate thresholds for thresholding is by using thresholding with hysteresis. This method uses multiple thresholds to find edges. We begin by using the upper threshold to find the start of an edge. Once we have a start point, we then trace the path of the edge through the image pixel by pixel, marking an edge whenever we are above the lower threshold. We stop marking our edge only when the value falls below our lower threshold. This approach makes the assumption that edges are likely to be in continuous curves, and allows us to follow a faint section of an edge we have previously seen, without meaning that every noisy pixel in the image is marked down as an edge. Still, however, we have the problem of choosing appropriate thresholding parameters, and suitable thresholding values may vary over the image.

Second-order approaches to edge detection

Some edge-detection operators are instead based upon second-order derivatives of the intensity. This essentially captures the rate of change in the intensity gradient. Thus, in the ideal continuous case, detection of zero-crossings in the second derivative captures local maxima in the gradient.

The early Marr- Hildreth operator is based on the detection of zero-crossings of the Laplacian operator applied to a Gaussian-smoothed image. It can be shown, however, that this operator will also return false edges corresponding to local minima of the gradient magnitude. Moreover, this operator will give poor localization at curved edges. Hence, this operator is today mainly of historical interest.

Differential edge detection

A more refined second-order edge detection approach, which also automatically gives edges with sub-pixel accuracy, is by using the following *differential approach* of detecting zero-crossings of the second-order directional derivative in the gradient direction:

Phase Congruency Based Edge Detection

A recent development in edge detection techniques takes a frequency domain approach to finding edge locations. Phase congruency (also known as phase coherence) methods attempt to find locations in an image where all sinusoids in the frequency domain are in phase. These locations will generally

III.CENTROIDAL VORONOI TESSELLATION METHODOLOGY

Image segmentation is a process of subdividing an image into smaller pieces. In particular, the elements in each piece share some common features, e.g., roughly the same color or same brightness. The edges are naturally the boundaries between different segments of the image. A digital image is often stored in the form of pixels, so an image can be regarded as a function defined on a domain $\Omega \leq R^N$ in the Euclidean space where the values of *u* represents the colors or the gray levels of the pixels. In this paper, we consider the most familiar images whose domains are 2-D rectangles, i.e., $\Omega \leq R^2$. We note all of the ideas and algorithms below can be easily applied to higher dimensional and nonrectangular images.

Let the values of represent the intensities of the digital image. Since the pixels of a digital image are usually indexed by integer pairs, we can treat *u* as a discrete function defined over a set of points with integer coordinates, i.e., the point (x,y)= (i,j) where (i,j) are integer pairs that range over the image domain. Thus, the domain of a rectangular image is an index set D = {(i,j): i=1,…..I,j= 1,……J} for some positive integers I and J

VORONOI DIAGRAMS

An ordinary Voronoi diagram is formed by a set of points in the plane called the generators or generating points. Every point in the plane is identified with the generator which is closest to it by some metric. The common choice is to use the Euclidean L_2 distance metric

$$|\mathbf{x}_1 - \mathbf{x}_2| = \sqrt{(x_1 - x_2)^2 + (y_1 - y_2)^2}$$

where $\mathbf{x}_1 = (x_1, y_1)$ and $\mathbf{x}_2 = (x_2, y_2)$ are any two points in the plane. The set of points in the plane identified with a particular generator form that generator's Voronoi region, and the set of Voronoi regions covers the entire plane.

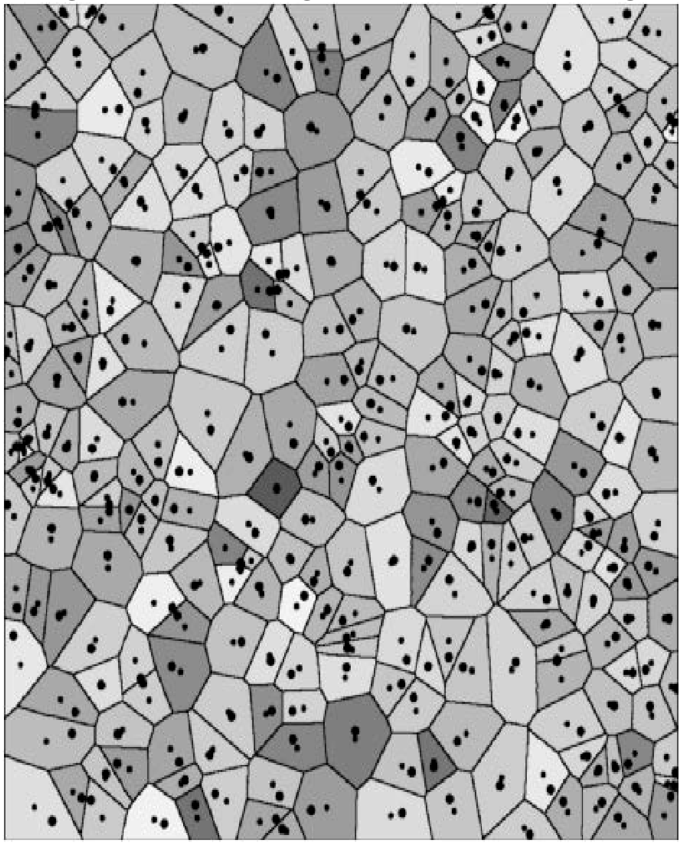


fig. Voronoi diagram with generators (large dots) and centroids (small dots)

CENTROIDAL VORONAI DIAGRAMS ALGORIHMS:

1. A centroidal Voronoi diagram has the odd property that each generating point lies exactly on the centroid of their Voronoi region. The centroid of a region is defined as

$$C_i = \frac{\int_A x\rho(x)dA}{\int_A \rho(x)dA} \tag{1}$$

where A is the region, $\mathbf{x}$ is the position and $\rho(\mathbf{x})$ is the density function. For a region of constant density ρ, the centroid can be considered as the centre of mass. Figure 1 has the centroids of each region marked with small circles.

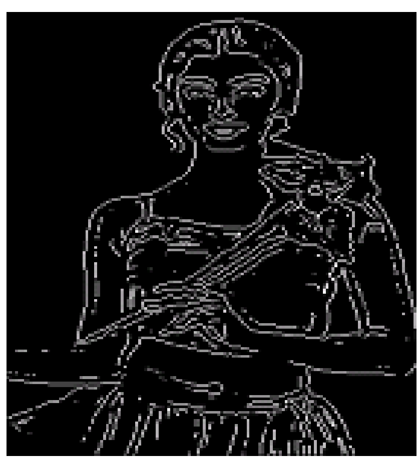
2. A centroidal Voronoi diagram is a minimum-energy configuration in the sense that it minimises $\int_A \rho(\mathbf{x})|\mathbf{C}_i - \mathbf{x}|^2$ .Practically speaking, a centroidal distribution of points is useful because the points are well-spaced in a definite sense.

EXPERIMENTS AND DISCUSSIONS:

The examples provided in the paper indicate that EWCVT-based methodologies are effective at several image processing tasks; the main goal of this paper was to present the EWCVT-based image segmentation edge detection methodologies and to provide some examples of their use. Here we have comparisons CVT-based methodologies seem to be very effective and are certainly much less costly to apply than, e.g., partial differential equation or variationally based methodologies. Of course, this paper EWCVT effectively proved and given sharp output by use of the threshold values and determined through an optimization procedure. The Ewcvt based algorithms provide us an effective way to control the segmentation accuracy.

IMAGE – 1.0

Stage2. The output Image1using EWCVT Model (threshold optimization value = 0.006944)



Stage.1.The output Image by EWCVT Model (threshold optimization value = 0.003472)

Stage3.Deduction of Image1using EWCVT Model (threshold optimization value = 0.013889)

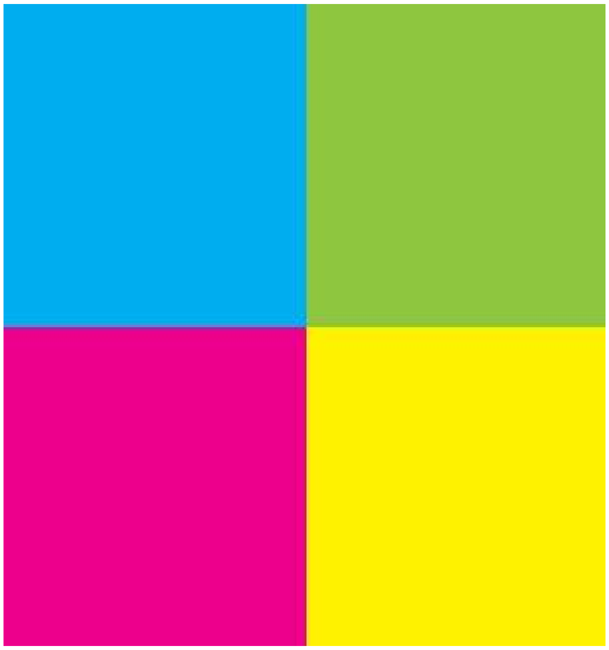
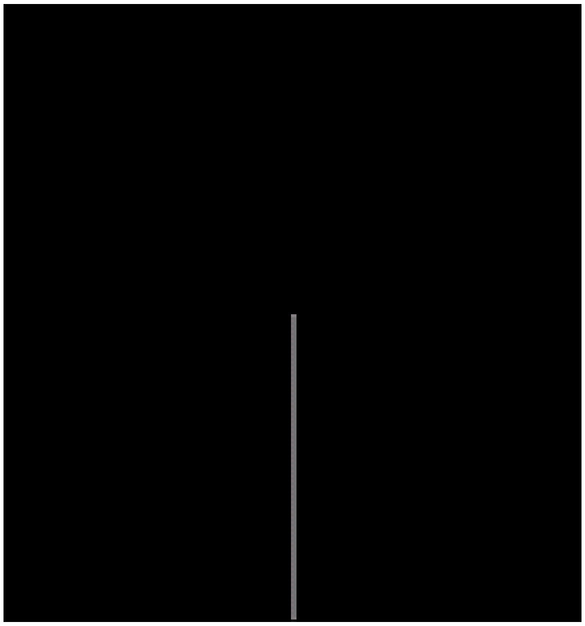
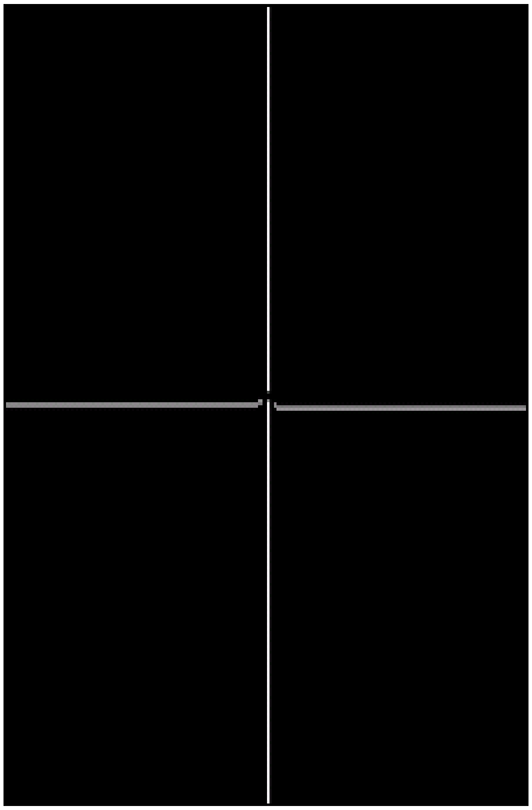


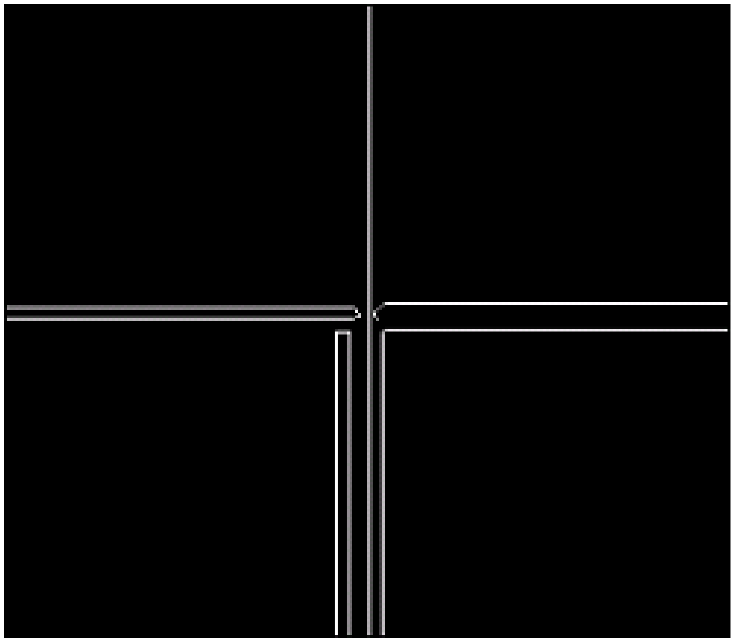
IMAGE – 2.0



Stage2. Deduction of Image1using EWCVT Model (threshold optimization value = 0.01047)

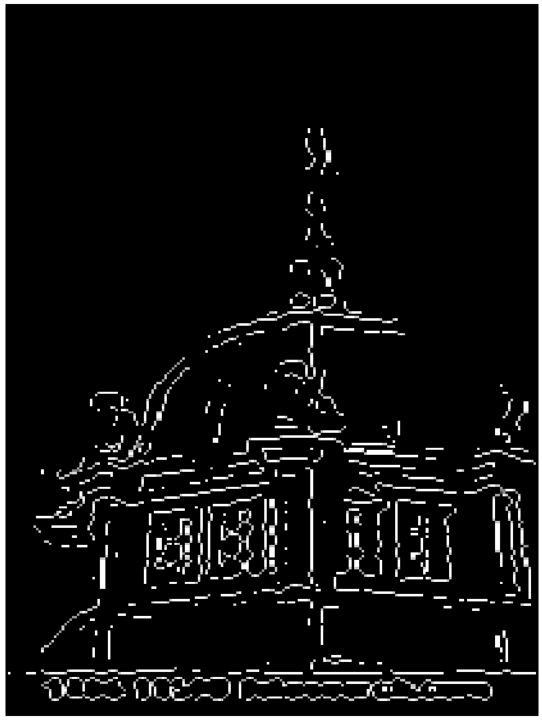


Stage1. Deduction of Image1using EWCVT Model (threshold optimization value = 0.006944)

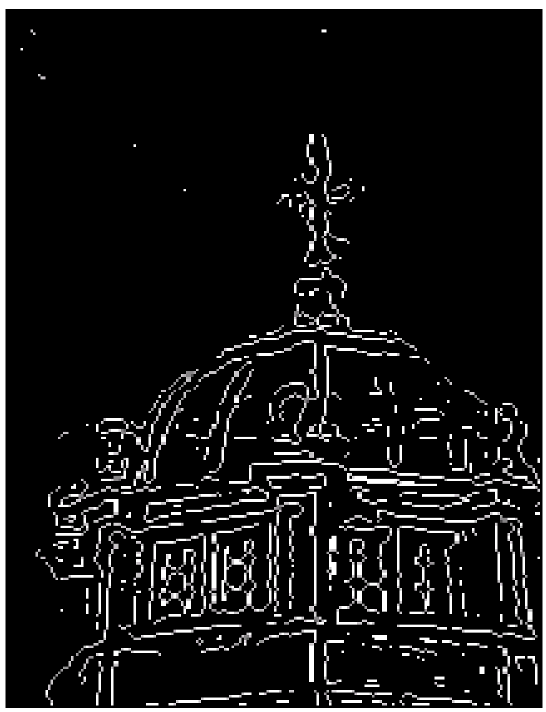


Stage3.Deduction of Image1using EWCVT Model (threshold optimization value = 0.00000)

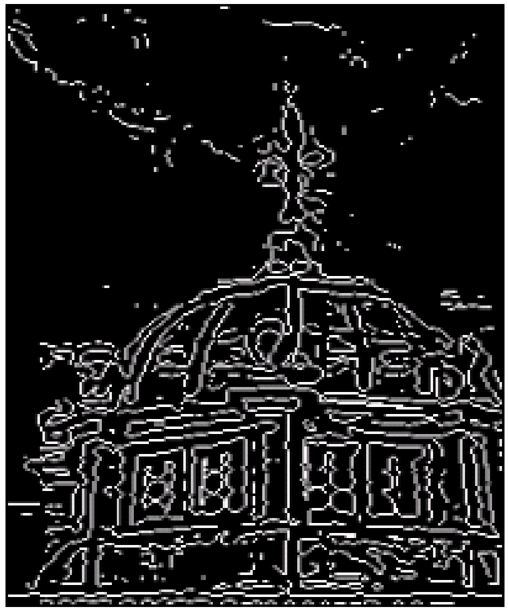
IMAGE – 3.0



Stage2.Deduction of Image1using EWCVT Model (threshold optimization value = 0.013889)



Stage1.Deduction of Image1using EWCVT Model (threshold optimization value = 0.006944)



Stage3.Deduction of Image1using EWCVT Model (threshold optimization value = 0.003472)

V. CONCLUDING REMARKS

In this paper, we generalize the basic centroidal Voronoi tessellation model for image segmentation to a new edge-weighted centroidal Voronoi tessellation model with efficient algorithms for its implementation in practical applications.

The EWCVT-based algorithms are essentially classical clustering algorithms so that they are often computationally less expensive than the popular and powerful partial differential equation based segmentation methods. Through extensive examples presented in the preceding section, we demonstrate many advantages of our method such as the efficiency in computational cost, the ability to handle any number of clusters, the robustness with respect to noises, and the flexibility to control the segmentation accuracy. Some of our future work includes the intensity inhomogeneous image segmentation and reconstruction of multichannel images based on our EWCVT model.

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