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IMAGE SEGMENTATION USING MULTICUE PARTIAL DIFFERENTIAL EQUATION

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Abstract —*In computer vision segmentation refers to the process of partitioning a digital image into multiple segments. The goal of segmentation is to simplify and change the representation of an image into something that is more meaningful and easier to analyze. The better quality of image segmentation results can be achieved by applying multiple cues such as intensity contrast, region size and texture using partial differential equation (PDE). We follow region based methodology either merge or suppress undesired regions so as to lead to the final result. Image simplification stage is concerned with noise and redundant information removal resulting in an image with smoother structure, easier to handle and more appropriate for further processing like feature extraction and partitioning. This can be achieved by applying Geometric filtering algorithm. A fast algorithm used to solve such PDEs is the FMM which provides an extremely fast way for solving eikonal equations. Every time we march a front one pixel forward, its area is incremented thus, the corresponding area term has to be updated.*

Keywords- *Segmentation; partitioning; Multicue; Partial differential equation; Image processing*

I. INTRODUCTION

Image segmentation remains an important, but hard-to-solve, problem since it appears to be application dependent with usually no a priori information available regarding the image structure. Moreover, the increasing demands of image analysis tasks in terms of segmentation results' quality introduce the necessity of employing multiple cues for improving image segmentation results. Its critical role is derived by the fact that it forms the basis for most subsequent image analysis tasks. It is commonly accepted that the term segmentation covers a wider range of image processing tasks than the final partitioning of the image plane into disjoint regions.

Image segmentation is one of the most important, yet complicated problems in the field of computer vision. Its critical role is derived by the fact that it forms the basis for mostsubsequent image analysis tasks. It is commonly accepted that the term segmentation covers a wider range of image processing tasks than the final partitioning of the image plane into disjoint regions. In this project, finds the segmentation problem as a set of procedures that need to be followed starting from the initial image and yielding the final partitioning perceived either as a region map or a segmentation boundary. Thus, the task of segmentation, independently of the method used to achieve the partitioning, can be divided into the following stages: i) image preprocessing, ii) feature extraction, and iii) partitioning into disjoint regions. The preprocessing stage encompasses a wide range of subtasks such as image simplification (enhancement, smoothing, noise reduction, redundant information removal) resulting in an image consisting mostly of flat and largeregions, as well as image decomposition into constituent parts. The feature extraction deals with gradient features computation, texture measurements, markers extraction (small homogeneous regions), whereas the final stage of partitioning is the application of the selected segmentation algorithm so as to produce a region map of the image. Many different segmentation methodologies have been proposed and, depending on their approach to the problem, can be characterized either as boundary-based methods relying on the information provided by the object/region boundaries, or region-based exploiting information provided by the entire regions (contrast, texture properties, etc). The watershed has several advantages, including proper handling of gaps and placement of boundaries at most significant edges.

In this project proposes a watershed-like segmentation scheme that couples contrast, size, and texture information driven by two separate image components: cartoon U (for contrast information) and texture . The modeling of the proposed scheme is done via PDEs using ideas from curve evolution and level sets. The implementation is done by using and adapting specialized level set methodologies, thus ensuring speed and reduced computational cost. Through a complete set of experimental results, we demonstrate the performance of the proposed segmentation scheme. Furthermore, we provide quantitative and qualitative criteria that substantiate the way the proposed methodology outperforms the established watershed transform.

II. METHODOLOGY

Many different segmentation methodologies have been proposed and, depending on their approach to the problem, can be characterized either as boundary-based methods relying on the information provided by the object/region boundaries, or region-based exploiting information provided by the entire regions (contrast, texture properties, etc). A

Well-known region based segmentation methodology, which has attracted the interest of many researchers for years, is the watershed transform. Watershed has several advantages, including proper handling of gaps and placement of boundaries at most significant edges. Region Growing offers several advantages over conventional segmentation techniques. Unlike gradient and Laplacian methods, the borders of regions found by region growing are perfectly thin (since we only add pixels to the exterior of our region) and connected. The algorithm is also very stable with respect to noise. Our region will never contain too much of the background, so long as the parameters are defined correctly. Other techniques that produce connected edges, like boundary tracking, are very unstable.

Intensity contrast and region size criteria with other perceptually meaningful image characteristics, such as texture, aiming at improved segmentation. Additionally, we aimat integrating the aforementioned ideas with PDE modeling. In order to strengthen the segmentation efficiency, we treat the segmentation problem as set of subtasks, emphasizing particularly on every segmentation stage, utilizing the most appropriate set of tools for the image processing tasks, considering also the fact that the quality of each stage's output affects the overall segmentation result.

III. IMAGE SEGMENTATION

For image simplification, decomposition and feature extraction read the image called field.jpg of size [fig.1] and convert the rgb image into gray scale image .apply Gaussian filter to separate row and column of the image.

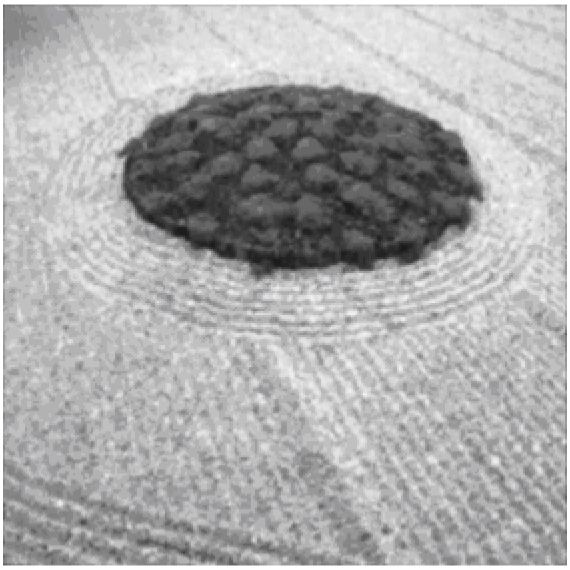


Fig1. Original Gray scale image

the simplification stage is concerned with noise and redundant information removal, resulting in an image with smoother structure, easier to handle and more appropriate for further processing such as feature extraction and partitioning. The filtering the image has to undergo should retain meaningful information but at the same time suppress pointless structures without causing boundary blurring or contour displacement. An efficient familyof filters that have the aforementioned properties are the morphological connected operators. These are region based filtering tools that do not modify individual pixel values but directly act on connected components of the space where the image is constant, referred to as flat zones. Intuitively connected operators can merge flat zones by removing boundaries between them, but cannot create new boundaries nor shift existing ones, therefore having very good contour preservation properties.

A. Contrast Filtering

The gray level reconstruction opening of an image I (x, y) given a marker signal for reconstruction opening and closing, repetitively. Symmetric simplification of image components requires self-dual filters, such as the levelings. Leveling preserve the coupling and sense of variation in neighbor image values and do not create any new regional maxima or minima across scales. In practice, they can reconstruct whole image objects with exact preservation of their boundaries and edges. After applying the contrast filter the image shown below.

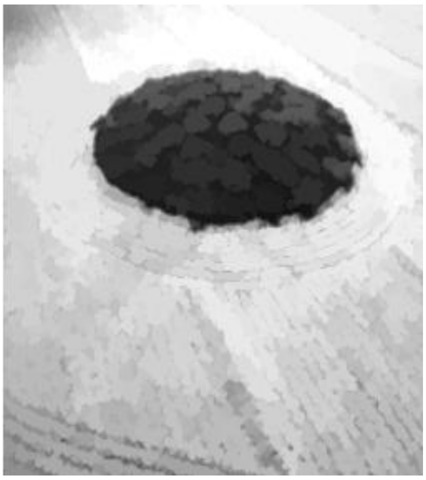


Fig2.Contrast filtered image

B. Levelings

The above reconstruction operators are asymmetric since they allow simplification of either bright or dark image components. Symmetric simplification of image components requires self-dual filters, such as the leveling, which are nonlinear, increasing, and idempotent filters with many interesting scale-space properties Leveling treat symmetrically the image foreground and background; further, they can be analyzed as composition of reconstruction opening and closing. They were defined geometrically via the property that the variation of the leveling between two neighbor pixels is bracketed by a larger same-sign variation in the reference image. It is defined algebraically as fixed points of iterated tri phase operators that switch among three phases, an expansion, a contraction, and the reference.

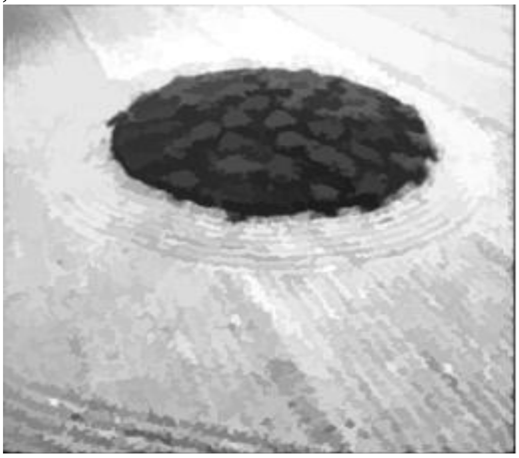
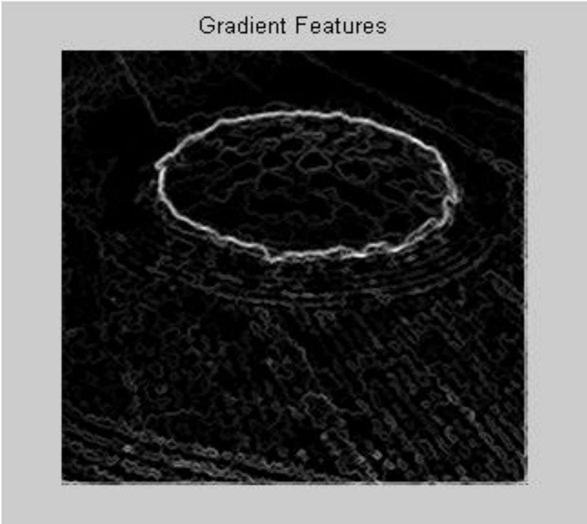


Fig.3 Levelled output

IV. FEATURE EXTRACTION

High values of the image's gradient are indicative of abrupt intensity changes and specify possible object/region contours. Additionally, the topographic relief, emerging from the gradient magnitude function is used in the flooding process, which, in turn, leads to the final segmentation map. Many different types of gradients have been extensively used in the edge detection framework. Among them, we choose the morphological gradient for its robust behavior, low complexity, and better segmentation results compared to other edge strength operators, such as $\| \Delta G\sigma * I \|$. The morphological gradient is computed as the magnitude of the dilated version of the image (after simplification) minus the eroded version of it, normalized by the diameter of the elementary structuring element used in the morphological operations.

We delineated a way of acquiring texture information from the observed image, under an image decomposition scheme. Although all appropriate information is theoretically contained in texture component, it is in a rough and unprocessed form. Therefore, we need a texture analysis and modeling scheme capable of quantifying texture characteristics. A way to model and analyze the existing texture patterns of an image is by assuming they are narrowband 2-D AM-FM signals. It provides both local and global texture information and tracks the most dominant texture components along multiple modulation bands The derived image textural feature is capable of quantifying important characteristics like geometrical complexity, rate of change in local contrast .



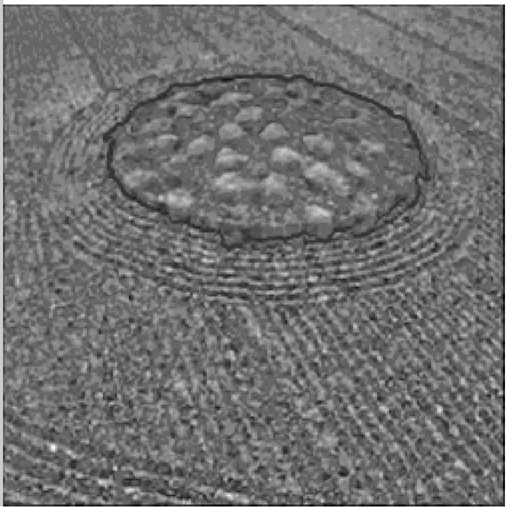


Fig4. Gradient features Fig5.Texture features.

An efficient way to estimate the 2-D amplitude and frequency signals was developed based on the energy operator. The product of the instantaneous amplitude and frequency magnitude square may be called the texture modulation energy. It is not directly applied on the wideband signal, but on narrowband versions of it, filtered through a 2-D Gabor filter bank. The 2-D Gabor filters are characterized by impulse response. The filters are uniformly arranged in the spatial frequency domain, in a polar wavelet-like tessellation, with equal and directional symmetric bandwidths and cover densely the frequency domain. Representations indicative of the dominant texture components are obtained by an energy tracking mechanism in the multidimensional feature space consisting of the filter responses. The filtered texture components are subjected to energy measurements via the 2-D Energy Operator. The energies are then averaged by a local averaging filter and are subjected to pixel wise comparisons. The derived image textural feature is capable of quantifying important characteristics like geometrical complexity, rate of change in local contrast variations and texture scale.

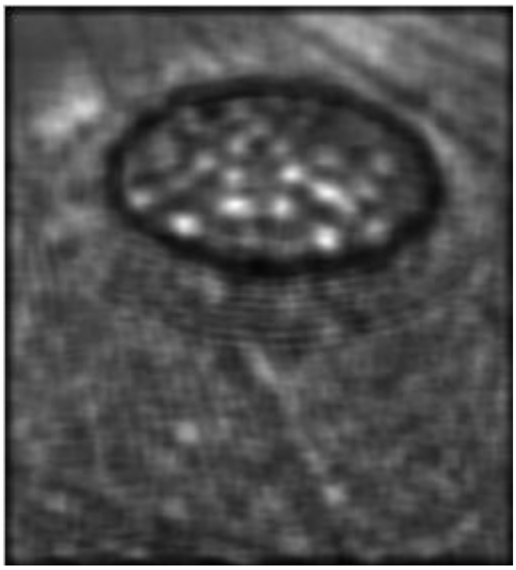


Fig 6. Teager energy of texture image

Markers are estimated as valleys (or peaks) of certain strength of a generalized bottom (top) hat transform defined as:, where is a generalized closing and is an intensity image (initial or simplified). Similarly, the top hat transform is where a generalized opening is. Depending on what kind of closing/opening transform we choose, we obtain: a) contrast markers if the generalized closing is based on reconstruction, i.e., that is where the parameter controls the contrast (valley depth); b) area markers if is area closing; c) volume markers if is volume closing, in which case contrast and area criteria are exploited.

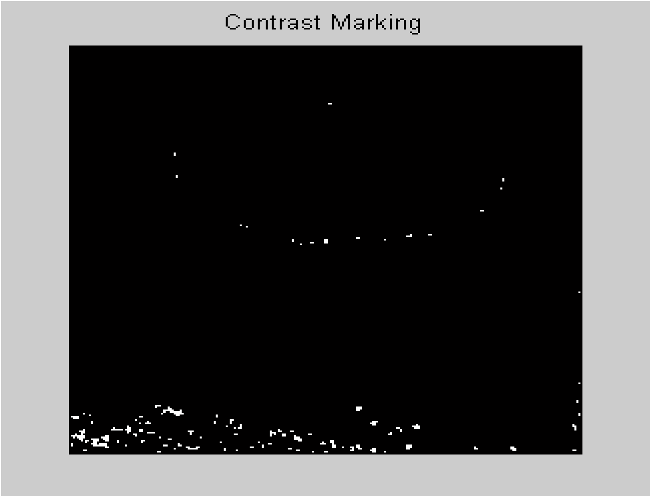


Fig7. Area, volume and contrast based markers

V. RESULTS

In mathematical morphology, the watershed transform is viewed as the flooding process of the topographic surface o the image, where the intensity defines the altitude of the relief. Flooding is achieved by immersing the surface into water, letting the water invade through pierced minima. The underlying idea is the following: a) a gradient image of the scene is constructed; b) for each object of interest or homogeneous region, marker is detected, either in an automatic or interactive manner; c) the watershed lines associated to the markers are constructed. The flooding process of image gradient surface starts with waves emanating from the set of markers, and at points where the waves meet each other, the segmentation boundaries are formed. Based on the criteria governing the flooding process, different types of segmentation can occur with varying characteristics in their results. By the term flooding criterion, we refer to the characteristic that all lakes (associated with the flooding sources) share with respect to water, such as altitude/height (contrast criteria), area (size criteria), or volume (contrast and area criteria). The most common type of flooding that forms the basis of all traditional morphological segmentation schemes is obtained when the water altitude variation is at the same level for all lakes, known as uniform height flooding. In the next paragraphs we investigate the classical case of uniform height watershed flooding and we introduce the case of uniform volume watershed flooding modeled via PDEs, where contrast and size criteria are balanced with respect to the topographic relief.

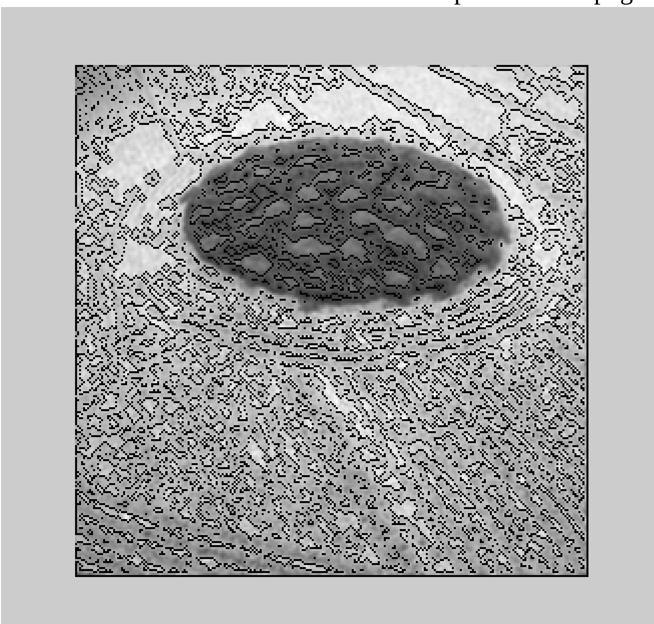


Fig8. Segmented image

VI. CONCLUSION

The performance of the proposed segmentation scheme is demonstrated through a complete set of experimental results and substantiated using quantitative and qualitative criteria. The problem of image segmentation as a set of subtasks, with emphasis on the image partitioning stage, viewed different information cues. Specifically, the stages of image simplification, decomposition into constituent parts and feature extraction were investigated, and connected operators of different types were proposed as the desirable tools for image pre-segmentation processing. Additionally, using ideas like image

Decomposition and texture AM-FM modeling, geometrical and textural information were coupled in a novel region growing watershed segmentation scheme. The proposed extended scheme was evaluated in terms of results' quality and was compared to other watershed-like segmentation methods. The obtained qualitative and comparative results verified the fact that the coupling of structural and textural information via decomposition, embedded in a generalized flooding segmentation procedure.

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