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Self similar texture segmentation

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Abstract: Texture segmentation is a task to discriminate between regions which have different textures.This work is poised on using the difference in mean, division and the third moment of various features such as orientation and contrast, further using the level sets method for extracting the homogeneous regions. The statistical features are extracted using a window of suitable size around each pixel .Here we are trying to explore the possibility of using windows of different shapes and their benefits on segmenting the textures.The work has done on IBM dial core system using MATLAB 7 software.

INTRODUCTION

Texture segmentation is a task to discriminate between regions which have different textures. Human visual system does this job of segmentation excellently with minimum effort. But this has been far from an easy one in image processing and computer vision. The problem is because of the non-availability of the universal mathematical model for real word textures.

Texture representation and modelling can be roughly divided into two categories: Statistical based approach and Filtering based approach [1]. Statistical modelling is based on the assumption that each texture has unique statistical attribute. The filtering model is based on applying some filter bank to the image and considering the filter's response has information about the local behaviour of the image. Popular choice is the Gabor filters. Most of the researchers who have worked previously on the texture segmentation have resorted to either Gabor scheme [2], the wave let approach [3], combination of statistical modelling; structural modelling and the filter bank model or morphology based multi-fractal estimation.

This work is poised on using the difference in mean, standard deviation and the third moment of various features such as orientation and contrast, further using the level sets method for extracting the homogeneous regions. The statistical features are extracted using a window of suitable size around each pixel. Here we are trying to explore the possibility of using windows of different shapes and their benefits in segmenting the textures. As this method uses the difference in the first order statistical quantity, it yields the results in lesser time and using of level sets makes this method a robust one.

Model based segmentation has been widely used in image processing that helps in extracting non-intensity described objects form images. Viz., natural images, medical images, etc. The technique involves interactively initializing a model curve in the image in the vicinity of the object to be segmented that will propagate towards the object boundary & help in solving segmentation problem

Efficient curve evolution algorithms have been proposed by researchers.

Identifying & capturing boundary information & embedding the same into curve evolution framework has become a research challenge. The challenge has been prevailing due to a large variety of possibilities existing in describing the boundary information in non-intensity described images. Current research will be aimed at finding this boundary information in a suitable way to be embedded into curve evolution framework for texture images.

Self-similar texture segmentation

When the images contain regions having very close similarity in their moment values like mean, variance and skewness, such images, having similar texture regions with very close statistical distribution of intensities have been termed as self-similar images. This work addresses the self-similar textured image segmentation issue using the statistical based approach for extracting the spatial structures.

Image processing

Modern digital technology has made it possible to manipulate multidimensional signals with systems that range from simple digital circuits to advance parallel computers. The goal of this manipulation can be divided into three categories

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• Image Processing: image in _: image out

• Image Analysis: image in _: measurements out

• Image Understanding: image in _:high-level description out

An image defined in the "real world" is considered to be a function of two real variables, for example, a(x,y) with a as the amplitude (e.g. brightness) of the image at the real coordinate position (x,y). A digital image is an image f(x,y) that has been discretised both in spatial coordinates and brightness. A digital image can be considered a matrix whose row and column indices identify a point in an image and the corresponding matrix element value identifies the gray level at that point. The elements of such a digital array are called image elements, picture elements, pixels opels with the last two being commonly used abbreviations of "picture elements".

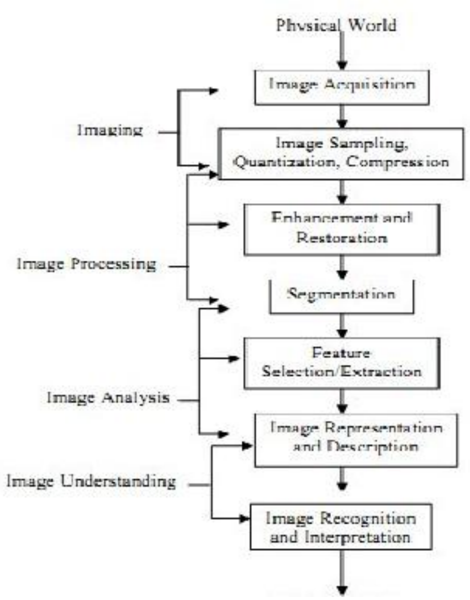

Figure 1: Image Processing and Analysis.

Fundamental steps in image processing

The first step in the process is image acquisition is to acquire a digital image. To do so requires an imaging sensor and the capability to digitize the signal produced by the sensor. The imaging sensor could also be a line-scan camera that produces single image line at time. In this case, the objects motion past the line scanned produces a two-dimensional image. If the output of the camera or other imaging sensor is not already in digital form, an analog to digital converter digitizes it.

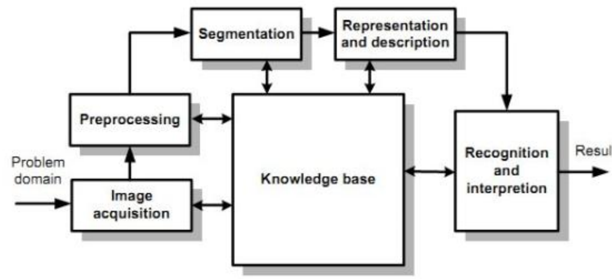

Figure 1.2 Image Processing Block Diagram

After a digital image has been obtained, the next step deals with preprocessing that image .The key function of preprocessing is to improve the image in ways that increases the chances of success of other process. Preprocessing typically deals with techniques for enhancing contrast, removing noise and isolating region**.**

The next stage deals with segmentation, segmentation partitions an input image into its constituent parts or objects. In general, autonomous segmentation is one of the most difficult tasks in digital image processing. On the one hand, rugged segmentation procedure brings the process a long way toward successful solution an image problem. On the other hand, weak or erratic segmentation algorithms all most always guarantee eventual failure. In terms of character recognition, the key role segmentation is extract individual characters and works from the background.

The output of the segmentation stage usually is raw pixel, constituting either the boundary of the region or all points in the region itself. In either case, converting the data to the form suitable for the computer processing is necessary. The first decision that must be made is whether the data should be represented as a boundary a complete region. Boundary representation is appropriate when the focus is on the external shape characteristics, such as corners and inflections. Regional representation is appropriate when the focus is on the internal properties, such as texture or skeletal shape in some applications, however these representations coexist. The situation occurs in character recognition applications, which often require algorithms based boundary shape as well as skeleton and other internal properties.

Representation is the only part of the solution for transforming the raw data into a form suitable for subsequent computer processing. A method must also be describing the data so that features of interest are highlighted. Description also called feature selection that deals with extracting features that result in some quantitative information of interest or features that are basic or differentiating one class of objects from another.

The last stage involves recognition and interpretation. Recognition is the process that assigns a label to an object based

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on the information provided by its descriptors. Interpretation involves assigning meaning to an ensemble of recognized objects [4].

Image segmentation

Segmentation is the process of partitioning an image into non-intersection regions such that each region is homogeneous and the union of no two adjacent regions is homogeneous.

Segmentation techniques locate objects consisting of pixels having something in common. Commonly this means that pixels with almost the same intensity values are grouped together, or pixels with the same colour code. Segmentation subdivides an image into its constituent regions or objects. The level to which this subdivision carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated. The key role segmentation is to separate foreground and background where foreground is interested or essential part of image and background is the uninterested part of image. In other words the goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier analyze.

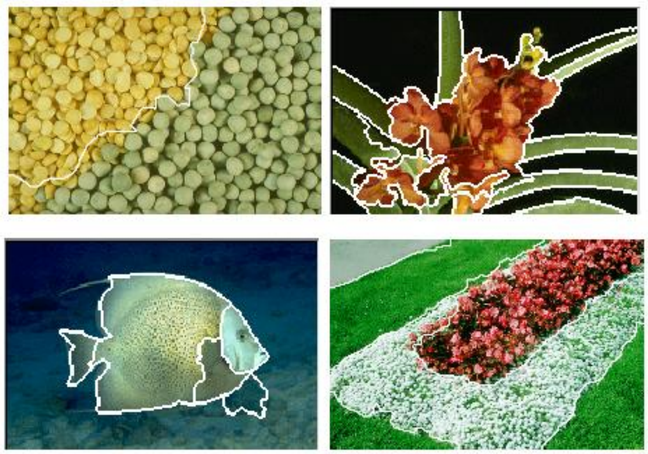

Figure 1.3 Some Examples for image segmentation

More precisely, image segmentation is the process of assigning a label every pixel in an image such that pixels with the same label share certain visual characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image. Each of the pixels in a region are similar with respect to some characteristic or computed property, such as color, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristic(s).

1. RELATED WORK

Segmentation techniques locate objects consisting of pixels having something in common. Commonly this means that pixels with almost the same intensity values are grouped together, or pixels with the same color code. There are techniques for finding objects with closed contours, convex objects and the boundaries of an object.

Segmentation techniques have not been widely applied, partly because they are time consuming and partly because there are no overall techniques that are suitable for all different types of images. All intensity based segmentation techniques are sensible to the situation that different objects have almost equal intensities. This will often lead to misclassification if the objects from the view of the human eye should not belong to the same class.

Texture image segmentation

Textures are one of the non-intensity described images. Segmenting texture described objects/regions has been useful in applications like, vision based medical image analysis, multispectral imagery, etc.,

Texture segmentation aims at discriminating between regions which have different textures. Human visual system does this job of segmentation excellently with minimum effort. But this has been far from an easy one amongst Image Processing and Computer Vision. The problem is because of the non-availability of the universal mathematical model for real world textures.

Texture representation and modeling can be roughly divided into two categories: Statistical based approach and Filtering based approach. Statistical modeling is based on the assumption that each texture has unique statistical attribute.

The filtering model is based on applying some filter bank to the image and considering the filter response has information about the local behaviour of the image.

Popular choice is the Gabor filters. Most of the researchers who have worked previously on the texture segmentation have resorted to Gabor scheme [2], the wavelet approach [3], combination of statistical modeling, structural modeling and the filter bank model or morphology based multi-fractal estimation.

Level set method

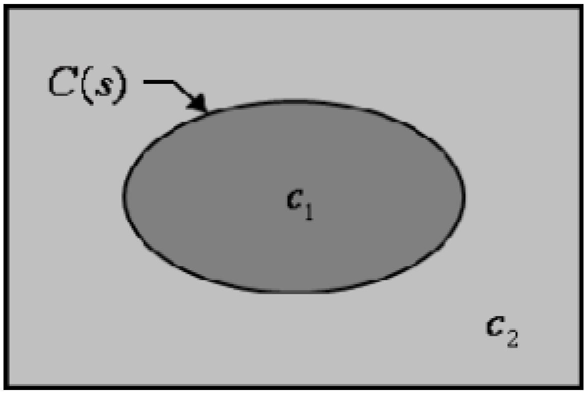

Figure 2.1 Level Set Diagrams.

Level set method employs curve evolution techniques. Level set is a higher dimensional distance mapped function embedding the deformable curve as reference zero valued level set. The curve used for segmentation is evolved using geometrical properties of the curve. The evolution is further coupled with the image data to recover the object boundaries. The model proposed by Chan and Vese [7], does not require the boundary descriptor of the image for the stopping process. The stopping term is based on Mumford – Shah's piece-wise model [8]. This model can detect contours with and without the edge descriptors. With this model the desired regions are automatically detected with the initial curve being anywhere in the image. Level set methods are capable of finding structures which are not determined by sharp gradients, a property which other segmentation techniques like edge finding by gradients are lacking.

If (x; t) is a level set function and zero level set evolves in time and is represented at any time t. The interface between the regions > 0 and < 0 is bounded by the zero level set as shown in the fig. above.

2. TEXTURE IMAGE SEGEMENTATION AND LEVEL SETS

TEXTURES

Texture is a repeating pattern of local variations in image intensity. It is a feature used to partition images into regions of interest and to classify those regions and it provides information in the spatial arrangement of colours or intensities in image characterized by the spatial distribution of intensity levels in a neighborhood. It is a repeating pattern of local variations in image intensity. Texture is a local neighborhood property and it describes something that has a surface that is not smooth but has a raised pattern on it.

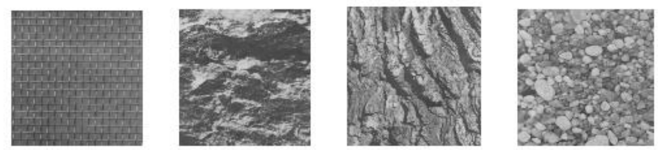

Figure 3.1 Different Types of Texture.

Texture consists of texture primitives or texture elements, sometimes called texels. Texture can be described as fine, coarse, grained, and smooth, etc. and such features are found in the tone and structure of a texture. Tone is based on pixel intensity properties in the texel, while structure represents the spatial relationship between texels. If texels are small and tonal differences between texels are large, a fine texture results. If Texels are large, and consist of several pixels, a coarse texture results.

For example, an image has a 50% black and 50% white distribution of pixels. Three different images with the same intensity distribution, but with different textures.

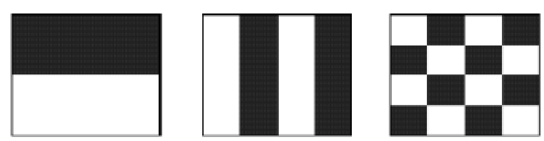

Figure 3.2 Different texture Images with same intensity

Segmentation of Textures – issues

A dictionary-like definition of texture segmentation would be the following:

``The partitioning of an image into regions, each of which contains a single texture distinct from its neighbors.'' However, this definition does little to explain the inherent difficulties and practical limitations involved in this problem. To start with, we should consider the two terms ``texture'' and ``segmentation'' separately.

Mathematically, image segmentation is well-defined. An image consists of an array of pixels, and we want to give each pixel a label. A region consists of a connected group of pixels that share the same label. But what constitutes a ``proper'' region?

Ideally, we would want each region to represent a different ``object" in the image. But what is an object? If a bookshelf is filled with books, do we want to consider each book as a separate object, or do we want the bookshelf and everything in it to be a single object? If we see a computer monitor sitting on a console with a keyboard attached to it, is there one object or three? It is clear, then, that there is no one segmentation of an image that can be considered to be ``right." The ``right" segmentation exists only in the mind of the observer, which can change not only between observers, but within the same observer at different times.

Even more slippery is the notion of texture. Whereas segmentation has at least a formal definition, texture has less of one. A typical definition in the literature is

``One or more basic local patterns that are repeated in a periodic manner." However, it is not clear exactly what the pattern is or how it is repeated. It is not even clear whether texture is an inherent property of all things, or whether some objects or regions lack texture altogether.

There are two approaches to defining texture, which may be thought of as ``top-down" and ``bottom-up." Top-down models claim that there is a basic element, called a Texel or a texton, and a placement rule, and the rule defines how and where the elements are placed. This definition works well if the texture consists of bricks piles of pennies. The bottom-up approach claims that texture is a property that can derived from the statistics of small groups of pixels, such as mean and variance. This works better for textures like quartz and grass where it is difficult to see individual elements. The dividing line between the two approaches is by no means clear.

Putting the two terms back together, we see the difficulties of the task. We wish to partition an image into regions of homogeneous texture, but we cannot always agree on when two texture samples are similar to each other. Furthermore, two different objects with a common boundary may have the same texture and be lumped together, which may or may not be desired. Texture segmentation will invariably break up certain objects which contain multiple textures, and group together pieces of different objects into one region.

Level sets

Level set methods provide mathematical and computational tools for tracking evolving interfaces with sharp corners and cusps, topological changes, and 3-D complications. Armed with these level set techniques, we can efficiently compute solutions to problems in geometry, fluid mechanics, and computer vision and material sciences.

Consider two separate circular flames, each burning outwards at a constant speed: the shape of the evolving interface is easily predicted.

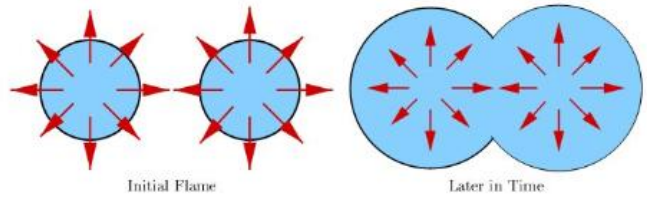

Figure 3.3 Initial Frame arising With Time

As the two separate flames burn together, the evolving interfaces merge into a single propagating front. However, a numerical algorithm based on a discrete parameterization runs into real trouble: in the figure below, the two pairs of buoys located inside the burned region must somehow be removed if we want to track the true edge of the expanding flam.

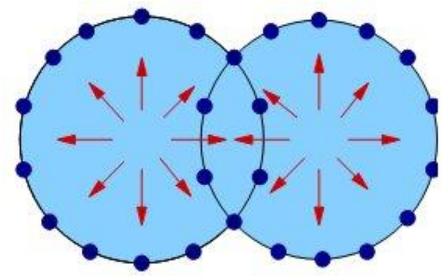

Figure 3.4 only edge buoys correspond to propagating interface

Paradoxically enough, the path to an efficient and versatile representation of propagating interfaces leads directly to the violent act of introducing a co-ordinate system. However, the trick is to do so in one higher dimension: this is the fundamental idea behind level set methods.

A level set representation

Rather than follow the interface itself, the level set approach instead takes the original interface and adds an extra dimension to the problem. Recalling the previous interface which consisted of two expanding circular blue flames, here we introduce a co-ordinate system, using the x-y plane which contains the interface, and a z direction to measure height.

Suppose we invent a function z= 3(x,y,t=0),just as was done previously to take as input a point

(x,y), and assigns a height z. This time, however, assign as height z the distance from (x,y) to the interface at time t=0.This builds a surface(shown in red) with the property that it intersects the xy plane exactly at the interface. The red surface is called the level set function, because it accepts as input any point in the plane and hands back a height as output. The blue interface is called the zero level set, because it is the collection of all points that are at height zero.

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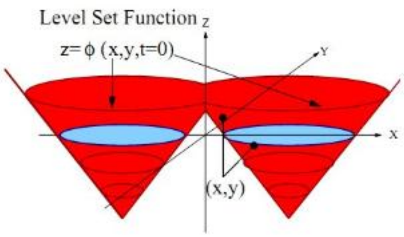

Figure 3.5 the level set surface (in red) plots the distance from each point (x.y) to the interface (in blue)

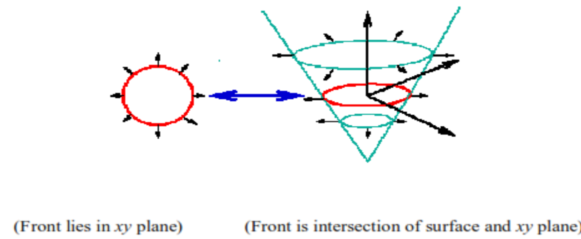

Figure 3.7Level set of information

Our plan is to figure out how to change the height of the surface 3(x,y,t) in time to match the evolution of the interface. The goal is to let the level set function expand, rise, fall, and do all the work: to find out where the interface is at any time, we can simply cut the surface at zero height, in other words, plot the zero contours.

Observe that in figure below, two expanding flames which merge into one simply means that the zero level set at a par11741ticular time becomes one curve rather than two.[6]

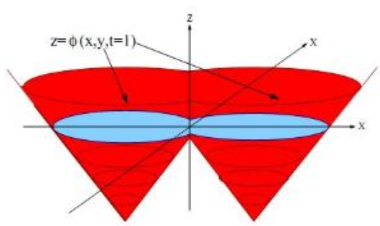

Figure 3.6Later in time: red level set surface has moved, yielding new blue interface

The reason it is called an "initial value formulation" is because the initial position of the interface gives initial data for a time-dependent problem i.e., the solution starts at a given position and evolves in time.

In other words, the level set approach introduced by Osher and Sethian instead takes the original curve (the red one on the left below), and builds it into a surface. That cone-shaped surface, which is shown in blue-green on the right below, has a great property; it intersects the xy plane exactly where the curve sits. The blue-green surface on the right below is called the level set function, because it accepts as input any point in the plane and hands back its height as output. The red front is called the zero level set, because it is the collection of all points that are at height zero

Chan and vese model:

Level set is a higher dimensional distance mapped function embedding the deformable curve as reference zero valued level set. The evolution which is due to geometrical properties of curve is further coupled with the image data to recover the object boundaries. The model proposed by Chan and Vese, does not require the boundary descriptor of the image for the stopping process. In simplest case, assume that the image I defined on Ω is composed of two regions separated by initialized model curve with homogeneous intensity values Ci and Co. Given a curve C that corresponds to boundary descriptor of the image I, they introduced homogeneity based function

$$E(C) = \int_{insideC} |I - c_i|^2 \, d\Omega + \int_{outsideC} |I - c_o|^2 \, d\Omega$$

Where, ci and Co are the average image intensities inside and outside of the model propagating curve C respectively. Assuming q to be the piece wise approximated model having intensity Co inside C and Ci outside C, it is easy to observe that q can be represented as

$$q = c_i H(\phi) + c_o(1 - H(\phi))$$

Where, the Heaviside function H(Φ) is defined as

$$H(\phi) = \begin{cases} 1, \phi > 0 \\ 0, \phi \le 0 \end{cases}$$

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Figure 3.8 Blue-initial curve, Red fore-ground

In above four figures, Left top indicates curve defined outside region interest, Left bottom indicates curve defined on region of interest, Right top indicates curve defined inside region of interest and Right bottom indicates segmented image. The minimum "energy" is obtained when the curve C being on the boundary of object. [7]

3. SEILF SIMILAR TEXTURES AND SEGMINTATION

In this proposed work, the above said moment descriptors are used as feature energy terms. Selection of appropriate feature becomes an important phase pre-segmentation. Global extraction of these features makes less sense as this will yield any measure of the distribution of intensities with respect to their spatial in neighborhood. Therefore the features are to be extracted within a local window suitable size around every pixel. The size of the window needs to be selected circumspectly because the larger window causes uncertainties along the region boundaries and the smaller window perhaps may fail to capture certain variations some of the textures. The precise descriptor and the correct size of the window are imperative attributes for good texture segmentation. In many unsupervised text segmentation procedures the process of feature and window size selection is more often than not done in a supervised way. In this work we are presenting a procedure for involuntary selection of window size.

With the functional in equation, the boundary between regions is defined by its extremum. To keep the curve functional continuously differentiable during evolution, regularizing terms based on the length and the area metrics of the curve added.

$$E(c_i, c_o, C) = \lambda_i \int_{insideC} |I - c_i|^2 d\Omega + \lambda_o \int_{outsideC} |I - c_o|^2 d\Omega + \mu \, length\,(C) + v \, area\,(C)$$

....

Translating the energy functional in equation to a higher dimensional level set function, one obtains

$$E(c_i, c_o, C) = \lambda_i \int_{\Omega} |I - c_i|^2 H(\varphi(d\Omega + \lambda_i \int_{\Omega} |I - c_o|^2 (1 - H(\varphi()d\Omega + \mu \int_{\Omega} \delta(\varphi) |\nabla \varphi| d\Omega + v \int_{\Omega} H(\varphi(d\Omega$$

This functional in equation (3.9) when subjected to minimization via Eulerian converts into motion PDE resulting into propagation of model curve. Thus the Eulerian of the energy functional in implicit level set form is reduced to

$$\frac{\partial \phi}{\partial t} = \left[\mu \nabla \bullet \left(\frac{\nabla \Phi}{|\nabla \Phi|} \right) + \alpha_1 (I_{ref} - c_i)^2 H(\phi) + \alpha_2 (I_{ref} - c_o)^2 (1 - H(\phi)) \right]$$

Where Φ is a signed distance function representing a continuously differentiable surface and I is replaced by I_{ref} image data for the texture image. The generalized expression for I_{ref} which represents the feature described which the combination of moment descriptors would be is

$$I_{ref} = (\alpha_1 * m_1)\ o_1\ (\alpha_2 * m_2)\ o_2 (\alpha_3 * m_3)\ o_3 \ldots\ldots\ldots (\alpha_n * m_n)$$

Where, the co-efficient α_i is between [0,1] and mi represents ith order moment. Similarly operator oi can be suitably chosen from the arithmetic operator set {+,-,*}.

Numerical Implementation

For the segmentation using level sets, the signed distance function is built using Euclidean distance metric. As the segmentation approach adopted is region based the curvature term is made redundant thus reducing time complexity.

The complete implementation thus uses a simplified level set motion PDE eliminating the curvature term. Further to have faster convergence random initialization of the model curve is used. The signed distance function can even be built using a scan and fill distance mapping technique [10] which reduces time complexity (even though execution time is not a prime factor in texture image segmentation)

Issue of Window Size and Shape

In general the window size also plays a decisive role for use of moment descriptors in segmenting texture regions. As the window size gets larger, more globe features are detected. This suggests that the choice of window size could possibly be tied to the contents of the image. The images with larger texture tokens would require larger window sizes whereas finer textures would require smaller windows. The window size may be even tied to the frequency content of image. However, the larger choice of window increases the uncertainty along the region boundaries. On the other hand if the window size is too small, it becomes

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difficult to capture the variations for certain textures. The execution time is less for small window sizes i.e., as the window size increases, the more time it takes for yielding a result.

The test image is divided into n equal sized partitions and mean of each partition is calculated. Starting with a smaller window say 3 X 3 located at the centre of the partition, increase the window size in steps till the mean of the window becomes equal to the mean of each partition. These window sizes are grouped into two clusters and mean of the sizes of the smaller cluster normally is the appropriate window size that could be used to extract the feature terms.

Issue of Selection of Moments

Lower order computationally non intensive statistical moments are used as feature energy terms to create the homogeneous neighborhood. The moments are vital attributes for good segmentation. The moments are calculated around each pixel within a suitable sized window. The first moment which is the mean gives out best features when the mean of the different regions are not same. If similar intensities are distributed within a region the second moment is selected as the feature energy term.

The second moment gives the spread of the distribution around the mean. For the regions with intensities that are symmetrically distributed about the mean, the third moment or skew gives the best feature energy term and is selected as the feature to embed into the level set frame work.

4. EXPERIMENTS AND RESULTS

In this work the examples presented are taken from Brodatz album (300 256x256 size) and combination of two texture regions is formed.

The task of unsupervised texture segmentation is found to be a challenging task because of the difficulty in locating the boundary of the textural regions. This happens mostly because of the similarity in textural content of the two regions under consideration. One of the ways to understand the similarity or dissimilarity between the textural regions could be through the statistical moment information of the target regions. The task of segmentation becomes more computationally rigorous when the images contain regions having very close similarity in their above said moment values. Such images, having similar texture regions with very close statistical distribution of intensities have been termed here as self-similar textures. the first moment quantifies the mean of the values of members belonging to a class. The second moment measures the deviation of the values of class members from their mean. It indicates the spread of the distribution around the mean. The third moment or the skew measures the non-symmetry of distribution of members around the mean. It is generally found that when more than one of these moments of the different regions of an image is same, then segmentation of such image which is termed here as self-similar becomes difficult and visually also such regions will be sometimes indistinguishable.

The mean value of the two regions namely D34 and D35 shown separately when combined will form an image with difference in mean and variances and skews being very close, which can be very well appreciated from the histograms of the two regions and also the values in the last column. Similarly the two regions D59 and D66 have the same mean and similar skew with difference in the second moment values.

An image with different skew and similarity in their second and third moment values is also presented in the last two rows.

For extracting the different texture regions in an image it is an obvious necessity to identify the textural properties or features which are instrumental in differentiating regions.

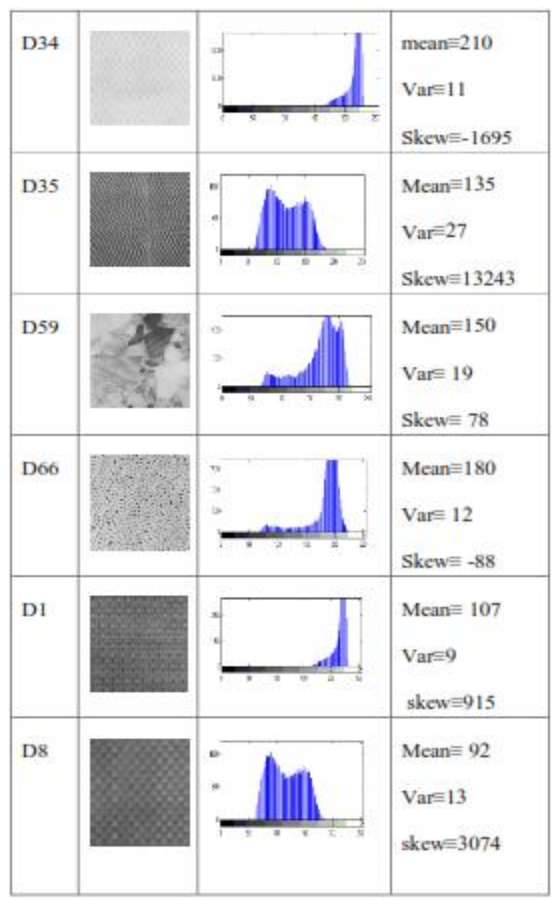

Figure 5.1 Images from brodatz album with their moment

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All results are presented using simplified motion PDE. The results are presented with combination of two texture regions derived from Brodatz's data base and some results are as shown below results. Each image below is internally arranged as follows: left side combination of images, right side histogram of individual images. Bottom left image is segmented images.

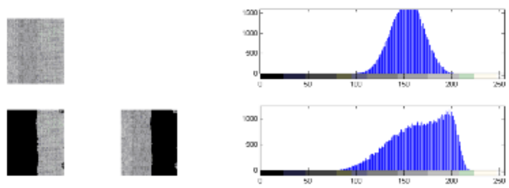

Fig a

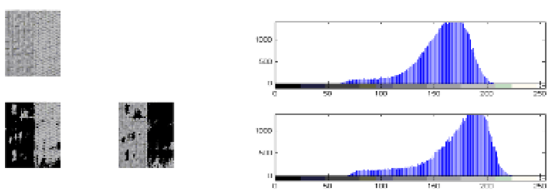

Fig b

The algorithm is implemented on IBM dual core PC using MATLA

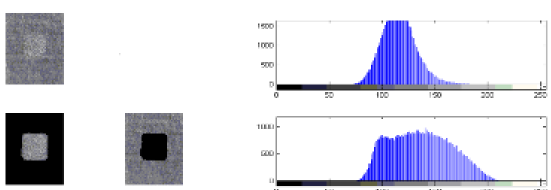

Fig c

Figure 5.2 results of some self similar images segmented and their histogram

The results are obtained using square window. The selection of size of the window is done heuristically.

5. CONCLUSION

In this paper, An integrated texture segmentation technique is presented that combines the power of simple moment descriptors and flexible cum accurate boundary extraction self similar images using level sets. The window size also plays a decisive role for use of moment descriptors in segmenting self similar texture regions. This proposed technique can be a better alternative to the computationally and time intensive texture segmentation techniques such as Gabor filters or wavelets.

Another interesting possibility could be to replace computationally intensive Euclidean metric by fast distance mapping metric like DSFT in level sets [10]. Further multiple self similar texture segmentation technique can be explored using multiphase level sets [11].

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