MEDICAL IMAGE ENHANCEMENT AND ROI

Gray scale Transforms

The gray level histogram of an image gives a global impression of the presence of different levels of density or intensity in the image over the dynamic range available. the histogram will indicate low levels of occurrences of certain gray level values or ranges .The given image may also contain large areas representing objects with certain specific ranges of gray level the histogram will then indicate large populations of pixels occupying the corresponding gray level ranges Based upon a study of the histogram of an image we could design grayscale transforms or look up tables LUTs that alter the overall appearance of the image and could improve the visibility of selected details.

Grayscale thresholding

When the gray levels of the objects of interest in an image are known or can be determined from the histogram of the given image, the image may be thresholded to obtain a variety of images that can display selected features of interest. For example if it is known that the objects of interest in the image have gray level values greater than L_1 we could create an image for display

$$g(m,n) = \begin{cases} 0 & \text{if } f(m,n) \leq L_1 \\ 255 & \text{if } f(m,n) \geq L_1 \end{cases},$$

where f (m,n) is the original image g(m,n)is the thresholded image to be displayed and the display range is [0,255].The result is a bilevel or binary image Thresholding may be considered to be a form of image enhancement in the sense that the objects of interest are perceived better in the resulting image . If the values less than L_1 were to be considered as noise and the gray levels within the objects of interest that are greater than L_1 are of interest in the displayed image, we could also define the output image as

$$g(m,n) = \begin{cases} 0 & \text{if } f(m,n) \leq L_1 \\ f(m,n) & \text{if } f(m,n) \geq L_1 \end{cases}.$$

The resulting image will display the features of interest including their gray level variations.

Grayscale windowing

If a given image f (m, n) has all of its pixel values in a narrow range of gray levels or if certain details of particular interest within the image occupy a narrow range of gray levels, it would be desirable to stretch the range of interest to the full range of display available. In the absence of reason to employ a nonlinear transformation, a linear transformation as follows could be used for this purpose:

$$g(m,n) = \begin{cases} 0 & \text{if } f(m,n) \leq f_1 \\ \frac{f(m,n)-f_1}{f_2-f_1} & \text{if } f_1 < f(m,n) < f_2 \\ 1 & \text{if } f(m,n) \geq f_2 \end{cases} ,$$

where f (m, n) is the original image g(m,n) is the windowed image to be displayed with its grayscale normalized to the range [0,1] and (f_1, f_2) is the range of the original gray level values to be displayed in the output after stretching to the full range .Note that the range [0,1] in the result needs to be mapped to the display range available, such as [0,255] which is achieved by simply multiplying the normalized values by 255. Details (pixels) below the lower limit f_1 will be eliminated (rendered black) and those above the upper limit f_2 will be saturated (rendered white) in the resulting image .The details within the range (f_1,f_2) will be displayed with increased contrast and latitude, utilizing the full range of display available.

Histogram Transformation

Based upon this property, the technique of histogram equalization has been proposed as a method to enhance the appearance of an image. Other technique have also been proposed to map the histogram of the given image into a different "desired" type of histogram, with the expectation that the Transformed image so obtained will bear an enhance appearances. although the method often do not yield useful results in biomedical applications and the underlined assumptions may not be applicable in many practical situations, histogram based methods for image enhancement are popular

Histogram Equalisation

Consider an image f(m,n) of size m,n pixels with gray levels l=0,1,2…..l-1.Let the histogram of the image be represented by P*f (l)* .Let us normalize the gray levels by dividing the maximum level available or permitted, as r=1/L-1 such that 0≤r≤1 .Let pf(r) be the normalized histogram .if we apply a transformation s=T(r) to the random variable r, the pdf of the new variable s is given by

$$p_g(s) = p_f(r)\,\frac{dr}{ds}\,\Big|_{r=T^{-1}(s)} ,$$

Where g refers to the resulting image g(m,n) with the normalized gray levels 0≤S≤1 .Consider the transformation

$$s = T(r) = \int^{r} p_f(w)\,dw; \quad 0 \leq r \leq 1.$$

This is the cumulative (probability) distribution function of r. T(r) has the following properties.

- $T(r)$ is single-valued and monotonically increasing over the interval $0 \leq r \leq 1$. This is necessary to maintain the black-to-white transition order between the original and processed images.
- $0 \leq T(r) \leq 1$ for $0 \leq r \leq 1$. This is required in order to maintain the same range of values in the input and output images.

It follows that $\frac{ds}{dr} = p_f(r)$. Then, we have

$$p_g(s) = \left[p_f(r) \frac{1}{p_f(r)} \right]_{r=T^{-1}(s)} = 1; \quad 0 \leq s \leq 1. \qquad (4.9)$$

Thus, $T(r)$ *equalizes* the histogram of the given image; that is, the histogram or PDF of the resulting image $g(m,n)$ is uniform. As we saw in Section 2.8, a uniform PDF has maximal entropy.

Thus t(r) equalises the histogram of the given image; that is, the histogram or pdf of the resulting image g(m,n) is uniform.

Discrete version of histogram equalization: for a digital image f(m,n) with a total of p=MN pixels and L Gray levels r_k,k=0,1,….,L-1,0≤r_k≤1, occurring n_k times, respectively ,the pdf may be approximated by the histogram

$$P\,f(r_k)=n_k/P; K=0,1,...L-1$$

The histogram equalizing transformation is approximated by

$$s_k = T(r_k) = \sum_{i=0}^{k} p_f(r_i) = \sum_{i=0}^{k} \frac{n_i}{P}; \; k = 0, 1, \ldots, L-1.$$

Histogram specification

A major limitation of histogram equalization is that it can provide only one output image, which, may not be satisfactory in many cases. The user has no control over the procedure or the result.Suppose that the desired or specified normalized histogram is Pd(t),with the desired image being represented as d,having the normalized gray levels t=0,1,2,…..L-1.Now ,the image *f with* the p*f(r)* may be histogram equalized by the transformation

$$s = T_1(r) = \int_0^r p_f(w)\, dw; \quad 0 \leq r \leq 1,$$

we also derive a histogram a equalizing transform for the desired image as

$$q = T_2(t) = \int_0^t p_d(w)\, dw; \quad 0 \leq t \leq 1.$$

Limitations of Global Operations

Global operators such as gray scale and histogram transforms provide simple mechanisms to manipulate the appearance of images. Some knowledge about the range of gray levels of the features of interest can assist in the design of linear or nonlinear LUTs for the enhancement of selected features in a given image. Although histogram equalization can lead to useful results in some situations, it is quite common to result in poor images. Even if we keep aside the limitations related to non unique transforms, a global approach to image enhancement ignores the non stationary nature of images and hence could lead to poor results. The results of histogram equalization of the chest X-ray and myocyte images demonstrate the limitations of global transforms. Given the wide range of details of interest in medical images, such as the hard tissues bone and soft tissues lung in a chest X-ray image, it is desirable to design local and adaptive transforms for effective image enhancement.

Local-area histogram equalization

Global histogram equalization tends to result in images where features having gray levels with low probabilities of occurrence in the original image are merged upon quantization of the equalizing transform and hence are lost in the enhanced image Ketchum attempted to address this problem by suggesting the application of histogram equalization on a local basis. In local_ area histogram equalization (LAHE) the histogram of the pixels within a sliding rectangular window centered at the current pixel being processed is equalized and the resulting transform is applied only to the central pixel the process is repeated for every pixel in the image. The window provides the local context for the pixel being processed. The method is computationally expensive because a new transform needs to be computed for every pixel

Adaptive neighborhood histogram equalization

A limitation of LAHE lies in the use of rectangular windows although such a window provides the local context of the pixel being processed, there is no apparent justification to the choice of the rectangular shape for the moving window Furthermore, the success of the method depends significantly upon proper choice of the size of the window the use of a fixed window of a prespecifed size over an entire image has no particular reasoning,Paranjape et al proposed an adaptive neighborhood approach to histogram equalization, As we saw the adaptive neighborhood image processing paradigm is based upon the identification of variable shape, variable size neighborhoods for each pixel by region growing. Because the region growing procedure used for adaptive neighborhood image processing leads to a relatively uniform region with gray level variations limited to that permitted by the specified threshold the local histogram of such a region will tend to span a limited range of gray levels Equalizing such a histogram and permitting the occurrence of the entire range of gray levels in any and every local context is inappropriate .In order to provide an increased context to histogram equalization Paranjape et al_ included in the local area not only the foreground region grown but also a background composed of a ribbon of pixels molded to the foreground. The extent of the local context provided depends upon the tolerance specified for region growing the transparency is created from the result. The original negative and the positive are held together and a positive print is made of the combination. The procedure leads to the subtraction of the local blur or fog component and hence to an improved

Convolution Mask Operators

Filtering images using convolution masks is a popular approach. Several such masks have been proposed and are in practical use for image enhancement. Equation demonstrates the use of a simple mask to represent the local mean filter.

Unsharp masking

When an image is blurred by some unknown phenomenon, we could assume that each pixel in the original image contributes in an additive manner, a certain fraction of its value to the neighboring pixels. Then each pixel is composed of its own true value_ plus fractional components of its neighbor's .The spreading of the value of a pixel into its neighborhood may be viewed as the development of a local fog or blurred background. In an established photographic technique known as unsharp masking, the given degraded image in its negative form is blurred and a positive transparency is created from the result, The original negative and the positive are held together and a positive print is made of the combination. The procedure leads to the subtraction of the local blur or fog component.

High frequency emphasis

Highpass filters are useful in detecting edges_ under the assumption that high frequency Fourier spectral components are associated with edges and large changes in the image. This property follows from the effect of differentiation

The ideal high pass filter:

$$H(U,V)=\{1 \text{ IF } D(U,V)\geq D_0, 0 \text{ otherwise}$$

The butterworth high pass filter:

$$H(u,v)=1/1+\sqrt{2}-1[D_0/D(u,v)]^{2n} \text{ where n is the order of the filter}$$

Adaptive Contrast Enhancement

Diagnostic features in medical images such as mammograms vary widely in size and shape Classical image enhancement techniques cannot adapt to the varying characteristics of such features. The application of a global transform or a fixed operator to an entire image often yields poor results in at least some parts of the given image It is therefore necessary to design methods that can adapt the operation performed or the pixel collection used to derive measures to the local details present in the image.

Adaptive neighbourhood contrast enhancement

Morrow proposed an adaptive-neighborhood contrast enhancement technique for application to mammograms. As we saw the adaptive-neighborhood or region-based image processing an adaptive neighborhood is defined about each pixel in the image the extent of which is dependent on the characteristics of the image feature in which the pixel being processed is situated. This neighborhood of similar pixels is called an adaptive neighborhood or region. Note that in image segmentation groups of pixels are found that have some property in common such as similar gray level and are used to define disjoint image regions called segments. Region-based processing may be performed by initially segmenting the given image and then processing each segment in turn, alternatively for region-based processing. We may define possibly overlapping regions for each pixel and process each of the regions independently Regions. If properly defined should correspond to image features Then features in the image are processed as whole units rather than pixels being processed using arbitrary groups of neighboring pixels for example masks. Region-based processing could also be designated as pixel-independent

Seed-fill region growing:

Morrow used a region-growing technique based on a simple graphical seed fill algorithm, also known as pixel aggregation. In this method, regions consist of spatially connected pixels that fall within a specified gray level deviation from the starting or seed pixels. For high resolution digitized mammograms, 4-connectivity was found, by visual comparison to be adequate to allow accurate region growing, although small features were better matched with 8-connected regions. The use of 8-connectivity for region growing requires longer computing time than 4-connectivity.

Homomorphic Filtering

If the image model is based on illumination-reflectance, then frequency domain procedures are not as easy to perform.

The main reason is that illumination and reflectance components of the model are not separable.

To be able to improve appearance of an image by simultaneous brightness range compression and contrast enhancement it is necessary to separate the two components.

As you recall, an image can be modeled mathematically in terms of illumination and reflectance as follow:

$$f(x,y) = I(x,y)\, r(x,y)$$

$$F\{f(x,y)\} \neq F\{i(x,y)\}\, F\{r(x,y)\}$$

- To accomplish separability, first map the model to natural log domain and then take the Fourier transform of it.

$$z(x,y) = \ln\{f(x,y)\} = \ln\{i(x,y)\} + \ln\{r(x,y)\}$$

Then,

$$F\{z(x,y)\} = F\{\ln i(x,y)\} + F\{\ln r(x,y)\}$$

or

$$Z(u,v) = I(u,v) + R(u,v)$$

➢ Now, if we process Z(u,v) by means of a filter function H(u,v) then,

$$S(u,v) = H(u,v)Z(u,v) =$$
$$= H(u,v)I(u,v) + H(u,v)R(u,v)$$

➢ Taking inverse Fourier transform of S(u,v) brings the result back into natural log domain,

$$s(x,y) = F^{-1}\{S(u,v)\}$$
$$= F^{-1}\{H(u,v)I(u,v)\} + F^{-1}\{H(u,v)R(u,v)\}$$

By letting

$$i'(x,y) = F^{-1}\{H(u,v)I(u,v)\}$$
$$r'(x,y) = F^{-1}\{H(u,v)R(u,v)\}$$

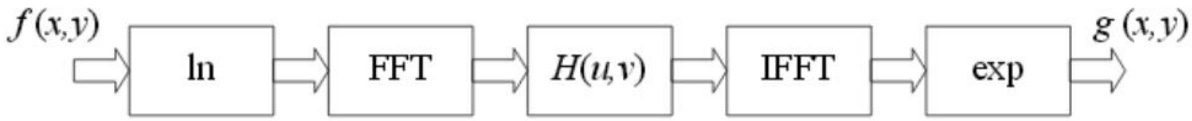
➢ Now, to get back to spatial domain, we need to get inverse transform of natural log, which is exponential,

$$s(x,y) = i'(x,y) + r'(x,y)$$
$$g(x,y) = \exp[s(x,y)]$$
$$= \exp[i'(x,y)] \cdot \exp[r'(x,y)]$$
$$= i_o(x,y)r_o(x,y)$$

Where $i_o(x,y)$ is illumination and $r_o(x,y)$ is reflectance components of the output image.

➢ This method is based on a special case of a class of systems known as *homomorphic systems*.

➢ The overall model in block diagram will look as follow:



➢ The illumination component of an image is generally characterized by slow spatial variation.

➢ The reflectance component of an image tends to vary abruptly.

➢ These characteristics lead to associating the low frequencies of the Fourier transform of the natural log of an image with illumination and high frequencies with reflectance.

➢ Even though these assumptions are approximation at best, a good deal of control can be gained over the illumination and reflectance components with a homomorphic filter.

Detection of Objects of Known Geometry

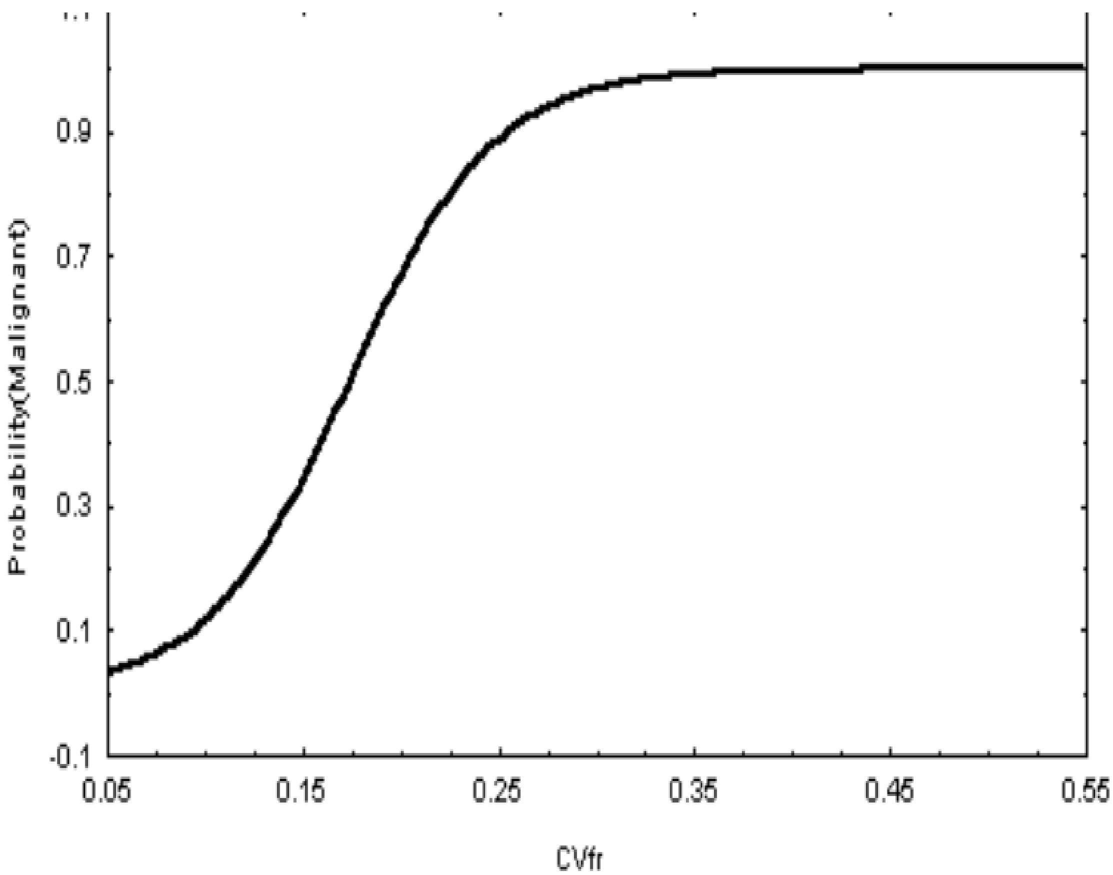
Occasionally, images contain objects that may be represented in an analytical form, such as straight line segments, circles, ellipses, and parabolas.

The Hough transform

Hough 358 proposed a method to detect straight lines in images based upon the representation of straight lines in the image (x,y) space using the slope-intercept equation

$$y=mx+c$$

Where m is the slope and c is the position where the line intercepts the y axis: see Figure(a). In the Hough domain or space, straight lines are characterized by the pair of parameters (m,c): the Hough space is also known as the parameter space. A disadvantage of this representation is that both m and c have unbounded ranges, which creates practical difficulties in the computation.



Detection of straight lines

Suppose we are given a digital image that contains a straight line. Let the pixels along the line be represented as $\{x(n), y(n)\},\ n = 0, 1, 2, \ldots, N-1,$ Where N is the number of pixels along the line. It is assumed that the image has been binarized, such that the pixels that belong to the line have the value 1 and all other pixels have the value 0. It is advantageous if the line is one pixel thick otherwise, several lines could exist within a thick line. If the normal parameters of the line are all pixels along the line satisfy the relationship

$$\rho_0 = x(n)\ \cos\theta_0 + y(n)\sin\theta_0.$$

Detection of circles

For example, all points along the perimeter of a circle of radius c centered at (x,y) =(a,b) satisfy the relationship

$$(x|-a)^2 + (y-b)^2 = c^2.$$

Methods for the Improvement of Contour or Region Estimates

- Polygonal and parabolic models
- B-spline and Bezier curves
- Active contour models or snakes
- The 'live wire'
- Fusion of multiple results of segmentation

Application Detection of the Spinal Canal

In an application to analyze CT images of neuroblastoma, the spinal canal was observed to interfere with the segmentation of the tumor using the fuzzy connectivity algorithm. In order to address this problem, a method was developed to detect the center of the spinal canal in each CT slice, grow the D region containing the spinal canal, and remove the structure. The initializing seeds for the region growing procedure were automatically obtained with the following procedure.

The outer region in the CT volume containing materials outside the patient, the skin, and peripheral fat was first segmented and removed .The CT volume was then thresholded at +800 HU to detect the high density bone structures. All voxels not within mm from the inner boundary of the peripheral fat layer were rejected, Regions were grown using each remaining voxels and all of the resulting regions were merged to form the bone volume. The inclusion criteria were in terms of the CT values being within +800±2σHU with Ў±σ= 103HU being the standard deviation of bone, and spatial Connectivity. The resulting CT volume was cropped to limit the scope of further analysis, as follows. The width of the image was divided into three equal parts, and the outer thirds were rejected. The height of the image was divided into six equal parts and the lower fourth and, fifth parts were included in the cropped region. In the interstice direction, the first 13% of the slices were removed, and the subsequent 20%slices were included in the cropped volume.

The cropped, binarized bone volume was subjected to a D derivative operator to produce the edges of the bone structures. The vertebral column is not continuous but made up of interlocking elements; As a result, the bone edge map could be sparse. The Hough transform for the detection of circles. The radius in the Hough space was limited to the range 6 to10mm. Because of the possibility of partial structures and edges in a given image, the global maximum in the Hough space may not relate to the inner circular edge of the spinal canal, as desired. In order to obtain the center and radius of the ROI, the CT values of bone marrow μ≈142HU and σ≈48HU and the spinal canal μ≈+30HU and σ≈8HU, were used as constraints. If the center of the circle corresponding to the Hough space maximum was not within the specified HU range, the circle was rejected and the next maximum in the Hough space was evaluated. This process was continued until a suitable circle was detected. The best fitting circle, which was not given by the global maximum in the Hough space, was obtained by applying the constraints defined above, The centers of the circles detected as above were used as the seed voxels in a fuzzy connectivity algorithm to segment the spinal canal. The mean and standard deviation required for this procedure were estimated using a7x7x2 neighborhood around each seed voxel.The spinal canal volume was then removed from the CT volume, resulting in improved segmentation of the tumor volume.

Application Detection of the Breast Boundary in Mammograms

Identification of the breast boundary is important in order to demarcate the breast region on a mammogram. The inclusion of this preliminary procedure in CAD systems can avoid useless processing time and data storage, By identifying the boundary of the breast, it is possible to remove any artifact present outside the breast area, such as patient markings ,(often high intensity regions) and noise, which can affect the performance of image analysis and pattern recognition techniques. Identification and extraction of the effective breast region is also important in PACS and telemammography systems. The profile of the breast has been used as additional information in different tasks in mammography. The skin air boundary information to perform density correction of peripheral breast tissue on digital mammograms, which is affected by the compression procedure applied during imaging. Chandrasekhar and Attikiouzel discussed the importance of the skin air boundary profile as a constraint in searching for the nipple location, which is often used as a reference point for registering mammograms taken at different times of the same subject. Other groups have used the breast boundary to perform registration between left and right mammograms in the process of detection of asymmetry. Most of the works presented in the literature to identify the boundary of the breast are based upon histogram analysis, which may be critically dependent upon the threshold selection process and the noise present in the image. Such techniques, as discussed by Bick et al, may not be robust for a screening application. Ferrari et al proposed active contour models, especially designed to be locally adaptive, for identification of the breast boundary in mammograms.

Application Detection of the Pectoral Muscle in Mammograms

The pectoral muscle represents a predominant density region in most MLO views of mammograms, and can affect the results of image processing methods. Intensity based methods, for example, can present poor performance when applied to differentiate dense structures such as the broglandular disc or small suspicious masses, because the pectoral muscle appears at approximately the same density as the dense tissues of interest in the image. The inclusion of the pectoral muscle in the image data being processed could also bias the detection procedures. Another important need to identify the pectoral muscle lies in the possibility that the local information of its edge, along with internal analysis of its region, could be used to identify the presence of abnormal auxiliary lymph nodes, which may be the only manifestation of occult breast carcinoma in some cases. Karssemeijer used the Hough transform and a set of threshold values applied to the accumulator cells in order to detect the pectoral muscle. Aylward et al,used a gradient magnitude ridge traversal algorithm at small scale, and then resolved the resulting multiple edges via a voting scheme in order to segment the pectoral muscle. Ferrari et al ,proposed a technique to detect the pectoral muscle based upon the Hough transform[8,10] which was a modification of the method proposed by Karssemeijer. However, the hypothesis of a straight line for the representation of the pectoral muscle is not always correct, and may impose limitations on subsequent stages of image analysis. Subsequently, Ferrari et al, proposed another method based upon directional altering using Gabor wavelets, this method overcomes the limitation of the straight line representation.

Application Improved Segmentation of Breast Masses by Fuzzy set based Fusion of Contours and Regions.

Given the difficult nature of the problem of the detection of masses and tumors in a mammogram, "the question arises?" Can the problem benefit from the use of multiple approaches?" Guliato et. al proposed two approaches to the detection problem: one based upon contour detection, and the other based upon a fuzzy region growing method. The former method is simple and easy to implement, always produces closed contours, and yields good results even in the presence of high levels of noise the latter produces a fuzzy representation of the ROI, and preserves the uncertainty around the boundaries of tumors .As a follow up, Guliato et. al; considered the following question. How may we combine the results of the two approaches; which may be considered to be complementary so as to obtain a possibly better result? In generic terms, the process of image segmentation may be defined as a procedure that groups the pixels of an image according to one or more local properties. A property of pixels is said to be local if it depends only on a pixel or its immediate neighborhood (for example, gray level, gradient, and local statistical measures). Techniques for image segmentation may be divided into two main categories: those based on discontinuity of local properties, and those based on similarity of local properties. The techniques based on discontinuity are simple in concept, but generally produce segmented regions with disconnected edges, requiring the application of additional methods, such as contour following. Techniques based on similarity, on the other hand, depend on a seed pixel (or a seed sub region) and on a strategy to traverse the image for region growing. Because different segmentation methods explore distinct, and sometimes complementary, characteristics of the given image, such as contour detection and region growing. it is natural to consider combinations of techniques that could possibly produce better results than any one technique on its own.