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Smoothing, Sharpening and Segmentation of Image

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Abstract— **In smoothing, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal. Sharpening is the process of creating or refining a sharp edge of appropriate shape on a tool or implement designed for cutting. Sharpening is done by grinding away material on the implement with an abrasive substance harder than the material of the implement, followed sometimes by processes to polish the sharp surface to increase smoothness and to correct small mechanical deformations without regrinding Image segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super-pixels). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.**

Index Terms— **Smoothing, Sharpening and Segmentation**

I. INTRODUCTION

In statistics and image processing, to smooth a data set is to create an approximating function that attempts to capture important patterns in the data, while leaving out noise or other fine-scale structures/rapid phenomena. In smoothing, the data points of a signal are modified so individual points (presumably because of noise) are reduced, and points that are lower than the adjacent points are increased leading to a smoother signal. Smoothing may be used in two important ways that can aid in data analysis (1) by being able to extract more information from the data as long as the assumption of smoothing is reasonable and (2) by being able to provide analyses that are both flexible and robust. Many different algorithms are used in smoothing. The image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). 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). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes.

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II. SMOOTHING AND SHARPENING

The step beyond transforming each pixel of a color image without regard to its neighbors is to modify its value based on the characteristics of the surrounding pixels. In this section, the basics of this type of neighborhood processing are illustrated within the context of color image smoothing and sharpening

A. Color Image Smoothing

Gray-scale image smoothing can be viewed as a spatial filtering operation in which the coefficients of the filtering mask are all 1's. As the mask is slid across the image to be smoothed, each pixel is replaced by the average of the pixels in the neighborhood defined by the mask. This concept is easily extended to the processing of full-color images. The principal difference is that instead of scalar gray-level values we must deal with component vectors of the form given in Equation (2).

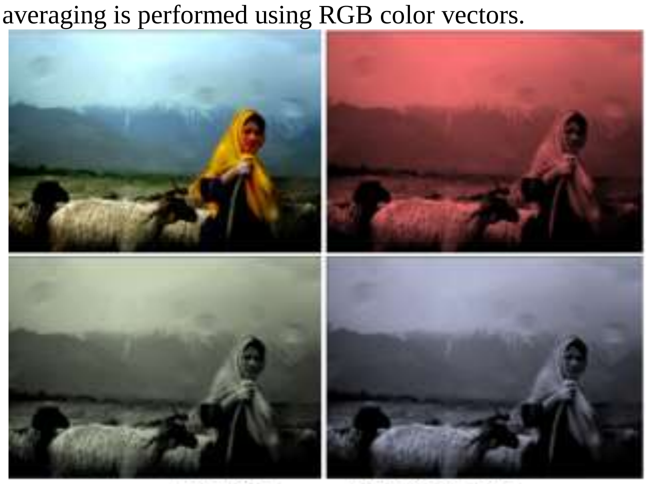
Let Sxy denote the set of coordinates defining a neighborhood centered at (x, y) in a RGB color image. The average of the RGB component vectors in this neighborhood is

$$\hat{c}(x, y) = 1/K \sum_{(x,y) Є sxy} c(x, y) \quad (1)$$

It follows from Equation (2) and the properties of vector addition that

$$\hat{c}(x, y) = \begin{bmatrix} 1/K \sum_{(x,y) Є sxy} c(x, y) \\ 1/K \sum_{(x,y) Є sxy} c(x, y) \\ 1/K \sum_{(x,y) Є sxy} c(x, y) \end{bmatrix} \quad (2)$$

When recognize the components of this vector as the scalar images that would be obtained by independently smoothing each plane of the starting RGB image using conventional gray-scale neighborhood processing. Thus, we conclude that smoothing by neighborhood averaging can be carried out on a per-color-plane basis. This result is the same as when the averaging is performed using RGB color vectors.



(a) RGB image (b) Red component image
(c) Green component (d) Blue component.

Figure 01 *Color Image Smoothing*

Eg:- Consider the color image shown in **Fig.01(a)**. The red, green, and blue planes of this image are depicted in Figs, **Fig.01(b)** through **(c)**.

Figures **Fig.01(a)** through **(d)** show the image's HSI components. We simply smooth independently each of the RGB color planes and then combine the processed planes to form a smoothed full-color result.

Figure 02 *HSI component of the RGB color image*

An important advantage of the HSI color model is that it decouples intensity (closely related to gray scale) and color information. This makes it suitable for many gray-scale processing techniques and suggests that it might be more efficient to smooth only the intensity component of the HSI representation in **Fig 02**. To illustrate the merits and/or consequences of this approach, we next smooth only the intensity component (leaving the hue and saturation components unmodified) and convert the processed result to an RGB image for display.

B. Color Image Sharpening

In this section we consider image sharpening using the Laplacian. From vector analysis, we know that the Laplacian of a vector is defined as a vector whose components are equal to the Laplacian of the individual scalar components of the input vector. In the RGB color system, the Laplacian of vector c in Equation is,

$$\nabla^2 [c(x, y)] = \begin{bmatrix} \nabla^2 R(x, y) \\ \nabla^2 R(x, y) \\ \nabla^2 R(x, y) \end{bmatrix},$$

which, as in the previous section, tells us that we can compute the Laplacian of a full-color image by computing the Laplacian of each component image separately.

Figure 03 Image *sharpening with the Laplacian.*

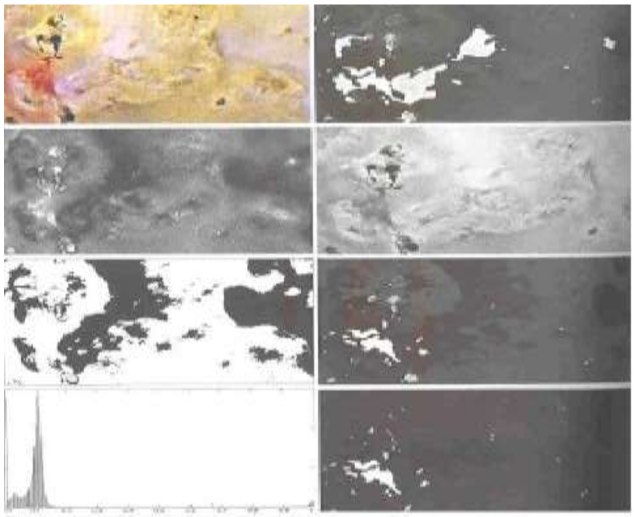
Eg:- **Figure 03** was obtained using Equation to compute the Laplacians of the RGB component images in **Fig. 01** and combining them to produce the sharpened full-color result. This result was generated by combining the Laplacian of the intensity component with the unchanged hue and saturation components.

III. Color Segmentation

Segmentation is a process that partitions an image into regions.

A. Segmentation in HIS color Space

If we wish to segment an image based on color, and, in addition, we want to carry out the process on individual planes, it is natural to think first of the HSI space because color is conveniently represented in the hue image. Typically, saturation is used as a masking image in order to isolate futher regions of interest in the hue image. The intensity image is used less frequently for segmentation of color images because it carries no color information. The following example is typical of how segmentation is performed in the HSI system.



a) Original, b) hue, c) Saturation, d) Intensity, e) Binary saturation mask(black=0), f) Product of (b) and (e), g) Histogram of (f), h) Segmentation of red components in(a).

Figure 04 Image *segmentation in HSI space*

Eg:- Suppose that it is of interest to segment the reddish region in the lower left of the image in **Fig. 04(a)**. Although it was generated by pseudocolor methods, this image can be processed (segmented) as a full-color image without loss of generality. **Figures 04 (b)** through **(d)** are its HSI component images.

Note by comparing **Fig 04(a)** and **(b)** that the region in which we are interested has relatively high values of hue, indicating that the colors are on the blue-magenta side of red. **Figure 04(e)** shows a binary mask generated by thresholding the saturation image with a threshold equal to 10% of the maximum value in the saturation image. Any pixel value greater than the threshold was set to 1 (white). All others were set to 0 (black).

Figure 04(f) is the product of the mask with the hue image, and **Fig 04(g)** is the histogram of the product image (note that the gray scale is in the range [0, 1]). We see in the histogram that high values (which are the values of interest) are grouped at the very high end of the gray scale, near 1.0. The result of thresholding the product image with threshold value of 0.9 resulted in the binary image shown in **Fig. 04(h)**. The spatial location of the white points in this image identifies the points in the original image that have the reddish hue of interest. This was far from a perfect segmentation because there are points in the original image that we certainly would say have a reddish hue, but that were not identified by this segmentation method However, it can be shown by experimentation that the regions shown in white in **Fig. 04(h)** are about the best this method can do in identifying the reddish components of the original image. The segmentation method discussed in the following section is capable of yielding considerable better results.

B. Segmentation in RGB vector Space

Working in HSI space is more intuitive, segmentation is one area in which better results generally are obtained by using RGB color vectors. The approach is straightforward. Suppose that the objective is to segment objects of a specified color range in an RGB image. Given a set of sample color point's representative of the colors of interest, we obtain an estimate of the "average" color that we wish to segment. Let this average color be denoted by the RGB vector **a** . The objective of segmentation is to classify each RGB pixel in a given image as having a color in the specified range or not. In order to perform this comparison, it is necessary to have a measure of similarity. One of the simplest measures in the Euclidean distance. Let **z** is similar to **a** if the distance between them is less than a specified threshold, *D0*. The Euclidean distance between **z** and **a** is given by

$$D(z, a) = \| z - a \|$$
$$= [(z - a)^T (z - a)]^{½}$$
$$= [(z_R - a_R)^2 + (z_G - a_G)^2 + (z_B - a_{\mathbf{B}})^2]^{½} \qquad (1)$$

where the subscripts R, G, and B, denote the RGB components of vectors **a** and **z.** The locus of points such that $D(z, a) \leq D0$ is a solid sphere of radius *D0* as illustrated in Fig. [05(a)]. Points contained within or on the surface of the sphere satisfy the specified color criterion; points outside the sphere od not. Coding these two sets of points in the image with, say, black and white, produces a binary segmented image.

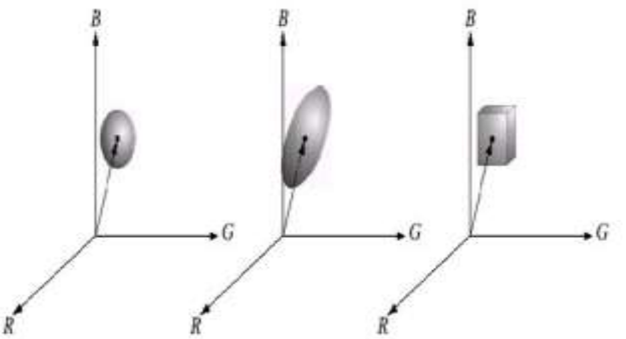


Figure 05 *Three approaches for regions for RGB vector segmentation.(a->b->c)*

A useful generalization of Equation. (1) is a distance measure of the form

$$D(z, a) = [(z - a)^T C^{-1} (z - a)]^{½} \qquad (2)$$

when C is the covariance matrix† of the samples representative of the color we wish to segment. The locus of points such that $D(z, a) \leq D0$ describes a solid 3-D elliptical body [Fig.05(b)] with the important property that its principal exes are oriented in the direction of maximum data spread. When C = I, the 3 * 3 identity matrix, Equation. (2) reduces to Equation (1). Segmentation is as described in the preceding paragraph.

Because distances are positive and monotonic, we can work with the distance squared instead, thus avoiding root computations. However, implementing Equation. (1) or (2) is computationally expensive for images of practical size, even if the square roots are not computed. A compromise is to use a bounding box, as illustrated in **Fig. [05(c)]**. In this approach, the box is centered on **a**, and its dimensions along each of the color axes is chosen proportional to the standard deviation of the samples along each of the axis. Computation of the standard deviations is done only once using sample color data.

Given an arbitrary color point, we segment it by determining whether or not it is on the surface or inside the box, as with the distance formulations. However, determining

(a) Original image with colors of interest shown enclosed by a rectangle.
(b) Result of segmentation in RGB vector space.

Figure 06 Segmentation *in RGB space*

whether a color point is inside or outside the box is much simpler computationally when compared to a spherical or elliptical enclosure.

Eg:- The rectangular region shown **Fig. 06(a)** contains samples of reddish colors we wish to segment out of the color image. This is the same problem we considered using hue, but here we approach the problem using RGB color vectors. The approach followed was to compute the mean vector **a** using the color points contained within the rectangle in **Fig. 06(a),** and then to compute the standard deviation of the red, green, and blue values of those samples. A box was centered at **a**, and its dimensions along each of the RGB axes were selected as 1.25 times the standard deviation of the data along the corresponding axis. For example, let σ_R denote the standard deviation of the red components of the sample points. Then the dimensions of the box along the R-axis extended from $(a_R - 1.25\sigma_R)$ to $(a_R + 1.25\sigma_R)$, where a_R denotes the red component of average vector **a**. The result of coding each point in the entire color image as white if it was on the surface or inside the box, and as black otherwise, is shown in **Fig. 06(b)**. Note how the segmented region was generalized from the color samples enclosed by the rectangle. In fact, by comparing **Fig. 06(b)** and Fig. 04(h) , we see that segmentation in the RGB vector space yielded results that are much more accurate, in the sense that they correspond much more closely with what we would define as "reddish" points in the original color image.

IV. CONCLUSION

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 (see edge detection). 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). When applied to a stack of images, typical in medical imaging, the resulting contours after image segmentation can be used to create 3D reconstructions with the help of interpolation algorithms like marching cubes. Most segmentation methods are based only on color information of pixels in the image. Humans use much more knowledge than this when doing image segmentation, but implementing this knowledge would cost considerable computation time and would require a huge domain knowledge database, which is currently not available.

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AUTHOR'S PROFILE

Dr Mir Mohammad Azad was born in Village – Korer Betka; Post Office – Mirrer Betka; Police Station - Tangail; District - Tangail, Bangladesh on 10th October, 1982.He received PhD in Computer Science, 2008 from Golden State University, Master of Computer Application, 2006 from Bharath Institute of Higher Education and Research Deemed University (Bharath University) and Bachelor of Computer Application, 2004, Bangalore University, India. He also received Bachelor of Law (LL.B) from National University of Bangladesh. He was working as a lecturer and head of computer science in various colleges in Bangalore and also worked as an Assistant professor and Vice Principal in different colleges in Bangalore during the year (2005-2009).He worked as an Assistant Professor and Head of CSE & CSIT at Shanto Mariam university of Creative Technology (2010-2014). He is having 25 publications in international journal in various countries like UK, USA, FRANCE, KOREA, PAKISTAN, INDIA, GERMAN, and JAPAN. At present he is working as an Associate Professor, Department of Computer Science and Engineering, Department Computer Science and Information Technology in Shanto Mariam university of Creative Technology, Uttara, Dhaka, Bangladesh. His areas of interest include Computer Architecture, Architecture, E-commerce, Digital Image processing, Computer Network, Wireless communication, MIS and Law.

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