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OBJECT-BASED CONTRAST ENHANCEMENT

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ABSTRACT

Object-based contrast enhancement is a recently developed image processing technique which aims at improving the visibility of objects or features in images. The underlying concept is to identify objects in the image based on an object-defining criterion, hence the name "object-based contrast enhancement". The contrast of each object in the image with respect to its background is computed and replaced with a new increased value through a contrast transfer function, and the output pixel value is computed accordingly.

This thesis presents a detailed study on the object-based enhancement technique, with the main focus being placed on the development of a mathematical model for contrast, accurate object- and background-region growing techniques based upon the contrast model, the synthesis of optimal contrast functions, and dynamic range control. The differences between the object-based method and other well-established enhancement techniques are also analyzed and demonstrated by applications to a number of test images including mammograms. The object-based technique is found to be more effective than others in terms of whole-object enhancement, especially for low-contrast objects.

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Chapter 1

INTRODUCTION

1.1 MOTIVATION

Digital contrast enhancement is a field of image processing that aims at improving the visibility of features in images. The features could be coarse objects or fine details. The spectrum of contrast enhancement techniques is broad, covering spatial- and frequency-domain operations, global and local techniques, point operations and histogram-based transformations, and numerous variations and combinations of the above. A summary of these techniques and their usefulness will be described in Chapter 2.

Object-based contrast enhancement is a spatial-domain, local technique that aims at enhancing objects or features in images as whole entities, rather than enhancing only edges of the objects. The underlying concept is to identify objects in the given image based on an object-defining criterion. Initial developments in this direction were made by Gordon and Rangayyan [1] to enhance features present in mammograms (x-ray images of human breasts), specifically to identify clusters of calcification deposits that are associated with breast cancer. Among radiological images, the mammogram is one of the most difficult to interpret due to the low-contrast, small-size nature of malignant features; however, it is currently considered the most effective tool to detect nonpalpable cancer and early-stage cancer [2, 3, 4, 5]. For this reason, continuing research work is being conducted in this direction to enhance features in mammograms [6, 7, 8, 9, 10,11], and to analyze the shapes of diagnostic features [12].

The object-based contrast enhancement algorithm basically proceeds as follows: each object in the image is identified, its contrast is computed, a new contrast value is obtained through a contrast transfer function, and the object is assigned a new pixel value. Previous implementations of this method [1, 8] suffer from inaccurate approximation of objects and severe dynamic range expansion. The present thesis work was initiated to improve the technique and to make it a more generalized tool which could be applicable to a broad range of images.

1.2 THESIS OBJECTIVES

With regard to the development of the object-based contrast enhancement technique, the specific objectives of the thesis are as follows:

1. To develop a general mathematical model for object contrast as perceived by the human visual system, and a simplified model for low-contrast objects.

2. To establish object-region growing criteria based on the simplified contrast model.

3. To implement accurate object- and background-region growing techniques.

4. To evaluate the effectiveness of the region-growing criteria in noisy images.

5. To establish the required conditions for enhancement in terms of object size and background brightness variation.

6. To develop a new approach to optimize contrast enhancement functions, i.e., the synthesis of piecewise-linear enhancement functions.

7. To control the dynamic range expansion in the enhanced image.

1.3 THESIS OUTLINE

The objectives described in Section 1.2 are covered in this thesis as below:

- Chapter 2 discusses the concept of subjective contrast (i.e., as perceived by the human visual system), and how it can be modeled and defined mathematically. Contrast enhancement techniques are evaluated on the basis of visual contrast definition, with a focus on the enhancement of objects as whole entities.

- Chapters 3 covers the object- and background-region growing techniques (objectives 2 to 4).

- Chapter 4 describes in detail the steps of the object-based enhancement operation, including objectives 5 to 7.

- Chapter 5 illustrates the application of the algorithm to images of various types.

- Finally, Chapter 6 summarizes what the thesis has achieved as well as areas that could be improved in the future.

Chapter 2

CONTRAST MODELING AND EVALUATION OF CONTRAST ENHANCEMENT TECHNIQUES

In this chapter, a mathematical model for the subjective contrast (as perceived by the human visual system) is first established. The contrast enhancement techniques currently available are next evaluated in terms of object contrast enhancement based on the foundation of the contrast model. Finally, the object-based enhancement method is introduced and compared with other techniques at the conceptual level.

In this thesis, an image is represented by a two-dimensional function f(x,y), or simply f(P), where x and y are the rectangular coordinates of pixels in the image, and P represents the pixel at location (x,y). f(x,y) is referred to as the pixel value, or brightness value, or gray level at location (x,y) in the image. All input pixel values are assumed to be integers and greater than zero.

2.1 CONTRAST MODELING

In general terms, contrast refers to the difference in luminance between an object and its surrounding. In this thesis, an emphasis is placed on the *subjective* contrast, i.e., the psychovisual perception of the brightness difference.

The contrast sensitivity of the human visual system is characterized by examining the visibility of a uniform object placed in the center of a uniform background. The brightness difference between the object and its background is increased or decreased until the object becomes barely visible. The result is the well-known Weber's law, which states that for an object of brightness B to be distinguishable from the background of brightness (B+dB), the *relative* difference dB/B must be greater than a threshold value, which stays constant at about 2% for brightness levels ranging from 1 to 1000 Ft. Lambert [13, 14]. The just-noticeable threshold is also referred to as the Weber's ratio.

Based on the Weber's law, if the relative brightness difference |dB/B| between an object and its background is small and close to the Weber's ratio, the object contrast c can be approximately modeled as being proportional to |dB/B|:

$$c \cong \gamma\ |dB\ /\ B|, \tag{2.1}$$

where γ is a positive proportionality constant. Equation (2.1) is thus valid for brightness levels ranging from 1 to 1000 Ft. Lambert.

It is well known that the human visual system can adapt to an enormous range of brightness levels; however, it cannot operate over such a wide range *simultaneously* [13, 14]. Instead, it can simultaneously discriminate only brightness levels of a smaller range centered around an overall intensity that it adapts to under the given set of conditions. This phenomenon is known as *the brightness adaptation*, and the adapted intensity B_a is called the *brightness-adaptation level.*

As mentioned earlier, Weber's law applies to an object surrounded by a single background of brightness close to that of the object, in which case the adaptation level is approximately equal to the object (and background) brightness, i.e., $B_a \cong B$. As the adaptation level deviates from the object brightness, the just-noticeable threshold will vary accordingly. This effect can be examined by placing an object and its small background in another larger background such that the adaptation level now is approximately equal to the brightness of the larger background. The relative brightness difference dB/B between the object and its background is increased or decreased until the object becomes just visible, and the procedure is repeated for different values of B_a. The just-noticeable threshold is found to increase above the 2% value as the object brightness deviates from the adaptation level. More specifically, the just-noticeable threshold η is a logarithmic function of B/B_a [13]:

$$\eta \cong 0.02 + \delta \, | \log (B/B_a) | \tag{2.2}$$

where δ is a positive proportionality constant.

By the same token, as the object brightness becomes more different from the adaptation level, the object contrast decreases. Based on (2.2), the contrast can be approximately modeled as a logarithmic function of B/B_a. The contrast model (2.1) is modified to account for the effect of the adaptation level as follows:

$$c \cong \gamma \, |dB/B| - \lambda \, | \log (B/B_a) |, \tag{2.3}$$

where λ is a positive proportionality constant. Similar to (2.1), Equation (2.3) is valid for small values of $|dB/B|$ and for brightness levels between 1 and 1000 Ft. Lambert.

In a complicated image, as the eyes roam about the scene, the adaptation level does not remain the same; instead, it fluctuates in the same direction as the average brightness of the local scene. Thus it is necessary to obtain a method for estimating the adaptation levels for different objects in an image. Further study on the adaptation level, however, is beyond the scope of this thesis, and its effects on contrast will be ignored. The result of this simplification is that the final enhancement may not be satisfactory for objects with brightness being considerably different from the adaptation level.

The main focus of this thesis is the enhancement for low-contrast objects only; high-contrast objects are already visible and require less or no enhancement. For this reason, the use of the contrast models (2.1) or (2.3) can be extended for values of $|dB/B|$ which are higher than 2% but much smaller than unity. For high values of $|dB/B|$, the contrast models suffer some inaccuracy, which in turn affects the level of enhancement; nevertheless, this effect is not important since the object contrast is already high relatively.

From the foregoing discussion, the contrast model (2.1) will be used later in the thesis for contrast enhancement. If γ is chosen to be unity, (2.1) becomes

$$c \cong | dB / B |. \tag{2.4}$$

If the object and the background are uniform and their brightness values are equal to p_{ob} and p_{bg}, respectively, by (2.4), the object contrast can be defined by either one of the two following equations:

$$c = \frac{|p_{ob} - p_{bg}|}{p_{ob}}, \tag{2.5a}$$

$$c = \frac{|p_{ob} - p_{bg}|}{p_{bg}}. \tag{2.5b}$$

For low contrast, p_{ob} and p_{bg} are nearly equal and the two definitions yield almost the same result. To normalize contrast to the range [0, 1], c can be defined as [1]

$$c = \frac{|p_{ob} - p_{bg}|}{p_{ob} + p_{bg}}. \tag{2.6}$$

For low-level contrast, $p_{ob} \cong p_{bg}$. This gives

$$c \cong \frac{1}{2} \frac{|p_{ob} - p_{bg}|}{p_{ob}} \cong \frac{1}{2} \frac{|p_{ob} - p_{bg}|}{p_{bg}}. \tag{2.7}$$

The normalized contrast defined in (2.6) is thus proportional to the relative brightness difference with a scaling factor of 0.5. The definition in (2.6) will be used throughout the rest of the thesis.

2.2 EVALUATION OF CONTRAST ENHANCEMENT TECHNIQUES

2.2.1 Classification of Contrast Enhancement Techniques

Contrast enhancement techniques are grouped into two main classes: *spatial-domain* and *frequency-domain* operations. Spatial-domain operations deal with pixel values, whereas frequency-domain operations deal with the Fourier spectrum of the image. Well-known frequency-domain enhancement techniques are high-pass filtering and homormophic transformations that enhance high-frequency details and image sharpness [13].

Spatial-domain enhancement techniques are further classified into 3 categories: *point-operation*, *histogram-based*, and *local-neighborhood* techniques. The first type is based on linear gray level mapping and includes contrast stretching and windowing techniques [13]. The histogram-based technique is a non-linear gray level mapping procedure that is based on a transformation of the histogram of the given image. Common histogram techniques are histogram equalization and histogram modification [13]. The local-neighborhood technique operates upon an m x n neighborhood of the input pixel. A common application of this type is the enhancement of edges and high-frequency details [15, 16, 17]. Common operators are gradient-type filters which extract edges, and the unsharp masking operator, which enhances fine details [18, 19].

The point-operation and histogram techniques mentioned above are *global* in that the transformation is based upon the gray level distribution of the *entire* image. In general, they may fail to enhance local details, which may have little influence on the global transformation. To overcome this problem, the image is broken down into sub-images, and a separate transformation is applied to each sub-image. This gives rise to the local-processing counterparts, including local contrast stretching [20, 21], and local histogram equalization and modification [22, 23, 24].

2.2.2 Global Contrast Stretching

Contrast stretching, or simply stretching, is a spatial-domain mapping that linearly rescales input values so that the output values will occupy a specified larger range. If the input image f(x, y) is bounded within the range $[in_{min}, in_{max}]$, and the output image bounded within $[out_{min}, out_{max}]$, the required stretching transformation is

$$g(x,y) = k \cdot f(x,y) + b, \tag{2.8}$$

where

$$k = \frac{out_{max} - out_{min}}{in_{max} - in_{min}} > 1, \tag{2.9}$$

and

$$b = out_{min} - k\, in_{min}. \tag{2.10}$$

The parameter k defined in (2.9) is a measure of dynamic range expansion. Using the contrast definition (2.6), an expression for the contrast gain, g_c, can be obtained. Assuming $f(P_2) > f(P1)$, the input contrast corresponding to two pixels P_1 and P_2 is

$$c_{in} = \frac{f(P_2) - f(P_1)}{f(P_2) + f(P_1)},$$

and the output contrast is

$$c_{out} = \frac{g(P_2) - g(P_1)}{g(P_2) + g(P_1)} = \frac{k \cdot (f(P_2) - f(P_1))}{k\,(f(P_2) + f(P_1)) + 2b}.$$

c_{out} can be expressed in terms of c_{in} as

$$c_{out} = \frac{(f(P_2) - f(P_1)) / (f(P_2) + f(P_1))}{1 + \dfrac{2b}{k(f(P_2) + f(P_1))}}$$

$$= \frac{c_{in}}{1 + \dfrac{2b}{k(f(P_2) + f(P_1))}},$$

which leads to an expression for the contrast gain, g_c:

$$g_c = c_{out} / c_{in} = \frac{1}{1 + \dfrac{2b}{k(f(P_2) + f(P_1))}}. \tag{2.11}$$

Substituting (2.9) and (2.10) for k and b in (2.11) yields

$$g_c = \frac{1}{1 + \dfrac{2((out_{min} / k) - in_{min})}{f(P_2) + f(P_1)}}. \tag{2.12}$$

It is seen from (2.12) that the contrast gain is an increasing function of the dynamic range expansion measure, k. For contrast enhancement, g_c must be greater than unity. This requires

$$k > (out_{min} / in_{min}). \tag{2.13}$$

Hence to obtain contrast enhancement, k must be large enough to satisfy (2.13). This corresponds to dynamic range expansion. On the other hand, if k is small and does not satisfy (2.13), the contrast is decreased. This corresponds to dynamic range compression.

For contrast stretching to work, however, the output range must stay within the available range of the display equipment so that no clipping occurs. The main disadvantage of the stretching technique is that if the input range is already close to the display range, only negligible enhancement is obtained.

Another method often used to enhance contrast is *windowing*, which maps a certain sub-range of gray levels in the input image to a larger range, usually the available display range. In this case, features of gray levels within this sub-range are enhanced, while those outside it will be clipped. The stretching technique described earlier is a special case of windowing in that it maps the entire range, rather than a sub-range, of the input image. The disadvantage of windowing is that features are not enhanced equally, and multiple operations may be needed for different windows to bring out all features.

2.2.3 Global Histogram-Based Techniques

Histogram equalization is another common enhancement technique. It is basically a non-linear gray level transformation that tends to equalize the occurrences of all gray levels, producing a more uniform gray level histogram and maximum first-order entropy [13]. Under histogram equalization, an input gray level is transformed to a normalized output value (in the [0,1] range) equal to the cumulative distribution function of the input image evaluated at that input value. If the input image contains N pixels of M discrete values p_0, p_1, ..., p_{M-1}, with each value p_i occurring n_i times, i.e., with a probability of $q_i = n_i/N$, the normalized output values $\{ s_0, s_1, \ldots, s_{M-1} \}$ generated by the histogram-based technique will be

$$s_j = \sum_{i=0}^{j} q_i , \; 0 \leq j \leq M. \tag{2.14}$$

From (2.6) and (2.14), the contrast between two output values s_j and s_{j+k} is

$$c = \frac{s_{j+k} - s_j}{s_{j+k} + s_j} = \frac{\sum_{i=j+1}^{j+k} q_i}{\sum_{i=0}^{j+k} q_i + \sum_{i=0}^{j} q_i}. \tag{2.15}$$

For low contrast, $s_{j+k} \cong s_j$, and (2.15) becomes

$$c \cong \frac{1}{2} \frac{q_{j+1} + \dots + q_{j+k}}{q_0 + \dots + q_j} . \qquad (2.16)$$

Equation (2.16) shows that the output contrast is a function of the occurrences of the input pixel values and therefore is totally unrelated to the input pixel values and input contrast. The direction and amount of contrast change depend on the shape of the histogram of the input image. In other words, this technique may increase the visibility of certain low-contrast objects and, at the same time, have the opposite effect on others. There is no guarantee that all low-contrast details are enhanced. This limits the usefulness of the technique.

Histogram modification is more general than histogram equalization. The desired histogram of the enhanced image is first specified, and the required gray level transformation is then determined. This technique requires in advance a knowledge of the desired histogram. Compared to histogram equalization, it may result in more satisfactory images at the expense of multiple trials. In terms of object contrast enhancement, it suffers the same drawback as histogram equalization.

2.2.4 Localization of Global Transformations

Local contrast stretching is a technique that stretches the pixel values in an m x n pixel window using the local minimum and maximum of the windowed area [19, 20]. To reduce the amount of computation, the local extrema can be estimated using bilinear interpolation [20]. This method, however, is found to produce artifacts such as the average values of regions being brought closer together, and the manifestation of false regions in the presence of sharp gray level transition between two adjacent regions [20].

Local histogram equalization operates upon the local histogram of a pre-specified neighborhood centered at the input pixel. The gray level transformation derived from this local operation is used to compute the output pixel value. Approximation methods that speed up the operation have also been developed such as Adaptive Histogram Equalization and Moving Histogram Equalization [22, 23]. These methods calculate the output pixel values by bilinearly interpolating values that are obtained from a number of transformations. The local histogram techniques in general provide stronger contrast enhancement effect than their global counterparts because the localized histograms are adapted to local properties and occupy a smaller gray level range. However, they generate different kinds of artifacts depending on the interpolation method used, and, similar to the global histogram techniques, may still result in the loss of local details [23].

2.2.5 Local-Neighborhood Techniques

Unsharp masking is a common processing technique that enhances high-frequency details using local statistics. The input image f(x,y) is thought of as a linear combination of low-frequency and high-frequency components. The low-frequency component is taken as the average pixel value m(x,y) of a neighborhood centered at f(x,y), and the high-frequency component is taken as (f(x,y) - m(x,y)). The output pixel g(x,y) is related to the input pixel f(x,y) by the following relationship [15, 16, 17]:

$$g(x,y) = A\,[\, f(x,y) - m(x,y)\,] + m(x,y), \tag{2.17}$$

where A is the enhancement gain factor for the high-frequency component. Increasing A will have the effect of amplifying the local gray level variations. It can easily be shown that for objects larger than the neighborhood size, unsharp masking does not affect all the pixels in the objects. This is illustrated in Figure 2-1, which shows an object at location (x1, y1) encompassing the square neighborhood. The neighborhood is uniform because it is contained within the uniform object. Hence m(x1, y1) = f(x1, y1). From (2.17), g(x1, y1) = f(x1, y1) = m(x1, y1) regardless of A, i.e., the pixel value at (x1, y1) is unchanged.

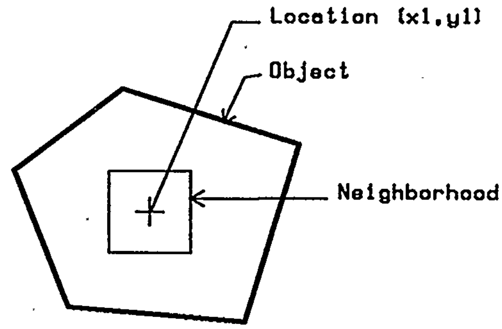

Figure 2-1 Illustration of an object encompassing the neighborhood used in unsharp masking operation

To make the local operations more effective, local statistics may be used to influence the parameters of the operations [15, 16, 19]. This gives rise to *locally adaptive* techniques, in which the operation parameters are adapted to local statistics. For example, the gain function A in the unsharp masking technique can be made inversely proportional to the standard deviation of the neighborhood. Since the standard deviation represents local contrast, the main effect will be high contrast gain for low-contrast features and low gain for high-contrast features.

2.3 OBJECT-BASED CONTRAST ENHANCEMENT

As mentioned in Chapter 1, the object-based contrast enhancement technique is a spatial-domain, local operation whose aim is to enhance objects as whole entities rather than enhancing only edges of the objects. For each pixel, the processing algorithm consists of five main steps [1, 8, 9, 10]:

1. Identify the object at the pixel location if it does exist.

2. Select a representative background.

3. Compute the contrast of the object with respect to the background.

4. Determine the new enhanced contrast by means of a contrast transfer function.

5. Compute the output pixel value corresponding to the new contrast.

Compared to other techniques, the object-based enhancement method has several potential advantages:

- The amount of enhancement, which depends on the local contrast, is not limited by the global extrema as in the case of global stretching.

- Unlike the histogram-based techniques, there is no loss of local objects.

- Artifacts such as those generated in local stretching and local histogram techniques do not exist.

- Whole-object enhancement is achieved as opposed to edge enhancement seen in local-neighborhood techniques.

The five processing steps in the object-based enhancement operation will be discussed later in detail, with steps 1 and 2 covered in Chapter 3, and the rest covered in Chapter 4. Application results for a number of test images will be presented in Chapter 5 to illustrate the usefulness of the object-based technique and the differences between various techniques.

2.4 SUMMARY

A general mathematical model for subjective contrast was established, and an approximate model was developed for the case of low-contrast objects whose brightness levels are not too different from the brightness-adaptation level. The common enhancement techniques were described and evaluated in terms of object contrast enhancement. At the conceptual level, the object-based technique was shown to be more effective than others. Deviations from the simplified contrast model caused by extreme brightness conditions outside the applicable range of the Weber's law and by the adaptation-brightness level were not studied in detail here; these topics, however, are important and need further investigation.

Chapter 3

REGION-GROWING TECHNIQUES

3.1 INTRODUCTION

This chapter discusses techniques to grow object and background regions required in the object-based contrast enhancement process. In this thesis, a *region* is understood as a *connected* set of pixels, and an *object* is defined as a connected region that is fairly uniform in brightness. Region growing is the procedure of grouping pixels or sub-regions of pixels into larger regions. A region-growing algorithm is characterized by its *pixel-grouping technique* and *region-growing criterion.* The pixel- grouping technique is the method by which pixels are selected for being examined if they should be included in the region. The examination is based upon an inclusion condition, which is referred to as region-growing criterion. For the purpose of growing uniform regions, it is necessary to define the uniformity of an object in a mathematical form, based upon which region-growing criteria can be developed.

The concepts of connectivity and connected regions, or simply regions, are summarized in the next section, followed by a description of the region-growing techniques that have been used in the past. The last two sections discuss respectively the object- and background-region growing techniques that are suitable for the object-based enhancement process.

3.2 DEFINITIONS OF CONNECTED REGIONS AND OBJECTS

The concept of connectivity between pixels is important in defining the boundaries of regions in an image. Its ramification is expressed through the following definitions [13]:

- Two pixels are said to be connected if they are neighbors of each other. The pixel located at (i,j) is said to be *4-connected* to the four pixels at locations (i, j-1), (i, j+1), (i-1, j), and (i+1, j), and *8-connected* to the 8 pixels at (i, j-1), (i, j+1), (i-1, j), (i+1, j), (i-1, j-1), (i-1, j+1), (i+1, j-1), and (i+1, j+1). Hence there are two types of connectivity, 4-connectivity and 8-connectivity. The term "connectivity" when used alone may refer to either type or both and should always be clearly specified.

- Pixels P and Q are said to be connected if there exists a path (N_0=P,...,N_m=Q) such that N_i is connected to N_{i-1}, for $1 \leq i \leq m$.

- A set of pixels R is said to be a connected region if every pair of pixels in R is connected.

In this thesis, an object is defined as a connected region of which every pixel must satisfy the specified uniformity criterion. The connectivity can be either 4-connected or 8-connected.

3.3 REVIEW OF REGION-GROWING TECHNIQUES

Region-growing techniques have been used in the past mainly for segmenting an image [13, 25, 26]. Image segmentation is the task of partitioning the given image into non-overlapping, connected sub-regions R_1, $R_2,\ldots,R_n$ such that each sub-region satisfies a region-defining criterion, and the union of any adjoining sub-regions does not. The region-defining criteria and the pixel-grouping techniques that have been used in the past are described next.

A region-growing criterion is often based on a definition of uniformity of a region. One common criterion defines a region R as a uniform one if

$$\sigma / m \leq L \tag{3.1}$$

where m and σ are the gray level mean and standard deviation of R respectively, and L is some chosen threshold. Another criterion defines region R in image f(P) (P represents a pixel) as a uniform one if [25]

$$\max_{P \in R} | f(P) - m | \leq t \tag{3.2}$$

where m is the average value of R, and t is some positive threshold value.

There are two common pixel-grouping techniques that have been used in the past; they are *pixel aggregation* and *split-and-merge* techniques [13, 25]. In pixel aggregation, region growing starts from a seed pixel. The algorithm examines each of the four- or eight-connected neighboring pixels of each boundary pixel of the existing region to determine if it can be included into the region without violating the region-growing criterion. The process continues until no more pixels can be included or a certain stopping condition is satisfied.

The split-and-merge technique has been used mainly for segmenting an image. Image segmentation is the task of partitioning an image into non-overlapping, connected sub-regions R_1, ..., R_n such that [13, 25]

$$\Phi(R_i) = \text{TRUE} \quad \text{for } i \in [1,n], \text{ and} \tag{3.3}$$

$$\Phi(R_i \cup R_j) = \text{FALSE} \quad \text{for } i \neq j,\ i \in [1, n],\ j \in [1, n], \tag{3.4}$$

where Φ is some logical region-defining criterion. The split-and-merge technique initially divides the image into an arbitrary set of non-overlapping connected sub-regions, then merges or splits the sub-regions in such a way that each resultant partition satisfies (3.3) and (3.4). At each intermediate step, the algorithm will *split* region R_i into four non-overlapping quadrants if $\Phi(R_i)$ = FALSE, and *merge* any adjacent regions R_i and R_j if $\Phi(R_i \cup R_j)$ = TRUE. The process stops when no further merging or splitting is possible. Numerous techniques have been developed to implement the split-and-merge algorithm [13, 25].

3.4 OBJECT-REGION GROWING TECHNIQUES

In the early development of the object-based enhancement technique, the object at each pixel location was approximated by a square centered at the pixel [1]. The square object region was grown step by step in size, and its contrast was computed. The background was chosen to be the region bounded between the square object region and a larger square of the same center. The region-growing process for each pixel ceased when the contrast stopped to increase. The main drawback of this approach is that the square-shape approximation does not truthfully represent objects of varying shapes. This causes errors in both the object and background approximations and consequently results in the distortion of object shapes. A more accurate method of growing object regions based on a suitable definition of uniformity is essential to avoid the distortion.

In the following sub-sections, two region-growing criteria are first developed based upon the contrast model presented in Chapter 2, followed by a comparison of the effectiveness of the two criteria. Finally, pixel-grouping techniques that are suitable for the region-growing criteria are discussed.

3.4.1 Object-Region Growing Criteria

To find an object-region growing criterion suitable for contrast enhancement, the definition of uniformity must be linked to the concept of contrast. A uniform region can be interpreted as having extremely small internal contrast, i.e., with negligible relative contrast between any two points in the region.

In light of the contrast definition provided in Section 2.1, it can be proved that the region-growing criterion (3.2) is not suitable for contrast enhancement application. If P_i and P_j are any points in the uniform region defined by (3.2), it follows that

$$m - t \leq f(P_i) \leq m + t, \tag{3.5}$$

$$\left| f(P_i) - f(P_j) \right| \leq (m + t) - (m - t),$$

or

$$\left| f(P_i) - f(P_j) \right| \leq 2t. \tag{3.6}$$

By (2.6), the contrast between P_i and P_j, c_{ij}, is

$$c_{ij} \cong \left| \frac{f(P_i) - f(P_j)}{f(P_i) + f(P_j)} \right|. \tag{3.7}$$

From (3.5) to (3.7), it is seen that c_{ij} is limited by an upper bound:

$$c_{ij} \leq \frac{2t}{2(m - t)},$$

or

$$c_{ij} \leq \frac{t}{m - t}. \tag{3.8}$$

Since c_{ij} represents the internal contrast between any two points in the region, the maximum allowed internal contrast for the region, c_{int_max}, is thus

$$c_{int\_max} = t / (m - t). \tag{3.9}$$

c_{int_max} is a strong function of the average value of the region, m. As m decreases, c_{int_max} increases, and the corresponding region will look less uniform. Hence the criterion (3.2) fails to produce regions of similar uniformity for a wide range of gray scale.

The criterion (3.2) must be modified to be consistent with the perceived contrast, especially in the low contrast range. Specifically, the *relative* -not the absolute- brightness difference between the pixel and the average brightness is to be compared against a positive threshold value T. The resulting condition is referred to as criterion A and is expressed below:

Criterion A:

$$\left| \frac{f(P) - m}{m} \right| \leq T. \tag{A}$$

Since $m > 0$, this condition is equivalent to

$$| f(P) - m | \leq mT. \tag{A1}$$

The selection of T is based on the allowed intrinsic brightness variations within objects. To find the maximum intrinsic variation, (A1) is first expanded to the equivalent form:

$$m (1 - T) \leq f(P) \leq m (1 + T). \tag{3.10}$$

The object pixel values are thus bounded by an upper and lower limit as seen in (3.10). The maximum intrinsic contrast, c_{int_max}, will be that between these two limits:

$$c_{int\_max} = \frac{| m (1+T) - m (1-T) |}{m (1+T) + m (1-T)},$$

$$c_{int\_max} = T. \tag{3.11}$$

Hence, the threshold T clearly divides the contrast range into two classes, with the lower range associated with intrinsic contrast which remains unchanged, and the higher one associated with object contrast which is to be enhanced. The equation (3.11) is used to select the threshold T based on a given value of c_{int_max}.

The criterion (A), which makes use of the average value of the region, may not be effective in the case of low-contrast objects with blurred boundaries. The main reason is the fact that the average value m is continuously updated after the inclusion of each intermediate pixel in the case of the pixel-aggregation technique, or after the forming of each new sub-region in the case of split-and-merge technique, making the criterion itself continuously changing. If m varies toward the background value, the net effect could be the inclusion of the background pixels in the object region. This is illustrated by the image in Figure 3-1, which shows a low-contrast object of value 100 at locations (i=2, j=2) and (i=3, j=2) over a background of value 103, with boundary pixels of value 102.

j \ i	0	1	2	3	4	5
0	103	103	103	103	103	103
1	103	102	102	102	102	103
2	103	102	100	100	102	103
3	103	102	102	102	102	103
4	103	103	103	103	103	103

Figure 3-1 Illustration of a low-contrast object with blurred boundary

If region growing starts at location (2, 2), by using (A) with $T = 2\%$, the neighboring pixels with a value of 102 will be included in the object region. As the process continues, more and more neighboring pixels are included, increasing the average value m of the object region. When the background pixels of value 103 are reached, m is 101.7. Based on (A), the background pixels of value 103 will be included in the object region. The criterion (A) thus fails to detect the object due to the transitional gray levels in the boundary.

In real images, the boundaries of the objects are often blurred, especially after the image undergoes a noise filtering operation such as mean or median filtering [13]. In such a case, to make the region-growing algorithm more effective for low-contrast objects, the average value m in (A) should be replaced by the starting pixel value $f(P_s)$. The modified criterion, referred to as criterion B, is

Criterion B:

$$\left| \frac{f(P) - f(P_s)}{f(P_s)} \right| \leq T \qquad \text{(B)}$$

If the input image is corrupted with additive random noise, both (A) and (B) may cause distortion to objects. In the following discussion, the probability of distorting objects in the case of (A) is determined first, and the result is then generalized for (B). To simplify the analysis, three assumptions are made: (1) the intrinsic brightness variations within each object are caused solely by noise, (2) the noise has a Gaussian distribution with a mean of zero and standard deviation σ, and (3) the object size is large enough such that its computed average value m can be considered as its true no-noise average. For the ease of calculation, a new variable z is introduced:

$$z = f(P) - m. \tag{3.12}$$

The probability density function of the noise, v(z), is

$$v(z) = \frac{\exp(-z^2 / (2\sigma^2))}{\sigma \sqrt{2\pi}} \tag{3.13}$$

The probability that the noise-corrupted value of f(P) differs from m by more than a positive value z_1 is given by

$$\text{prob}\,(|\,f(P) - m\,| > z_1) = \text{prob}\,(\,|z| > z1) \tag{3.14}$$

$$\text{prob}\,(|\,f(P) - m\,| > z_1) = \text{prob}\,(z < -z_1) + \text{prob}\,(z > z_1)$$

$$= \int_{-\infty}^{-z_1} v(z)\,dz + \int_{z_1}^{+\infty} v(z)\,dz \tag{3.15}$$

The first integral accounts for negative noise, and the second accounts for positive noise. The two integrals are equal because of the symmetry of the Gaussian probability density function about z=0, giving

$$\text{prob}\,(|f(P) - m| > z_1) = 2 \int_{z_1}^{+\infty} \frac{\exp(-z^2 / (2\sigma^2))}{\sigma \sqrt{2\pi}}\, dz. \tag{3.16}$$

The right-hand side of Equation (3.16) is known as the complementary error function, erfc $(z_1 / (\sqrt{2}\,\sigma))$:

$$\text{prob}\,(|f(P) - m| > z_1) = \text{erfc}\,(z_1 / (\sqrt{2}\,\sigma)). \tag{3.17}$$

Applying the above result to the uniform criterion (A1) yields the following error probabilities:

- The probability that an object pixel P is excluded from the object as a result of the added noise is

$$\epsilon_1 = \text{prob}\,(|f(P) - m| > mT) = \text{erfc}\,(mT / (\sqrt{2}\,\sigma)). \tag{3.18}$$

- The probability that an object of size N is distorted as a result of one or more excluded pixels is

$$\epsilon_2 = 1 - (1 - \epsilon_1)^N \tag{3.19}$$

$$\epsilon_2 = 1 - (1 - \text{erfc}\,(mT / (\sqrt{2}\,\sigma)))^N. \tag{3.20}$$

If $\epsilon_1 << 1$, (3.19) can be approximated by

$$\epsilon_2 \cong 1 - (1 - N\epsilon_1) = N\,\epsilon_1 = N\,\text{erfc}\,(mT / (\sqrt{2}\,\sigma)). \tag{3.21}$$

Figure 3-2 shows the probability density function for the case $\sigma = 2$. Error ϵ_1 is illustrated for the case $z_1 = mT = 3$. This error is equal to

$$\epsilon_1 = \text{prob}\,(|\,f(P) - m\,| > 3) = \int_{-\infty}^{-3} v\,(z)\,dz + \int_{3}^{+\infty} v\,(z)\,dz$$

and is shown as the shaded area in Figure 3-2. Numerical values of ϵ_1 and ϵ_2 are listed in Table 3-1 for several values of mT/σ and N.

From the above results, it is seen that the probability of causing distortion to an object is a decreasing function of mT/σ and increasing function of object size N. If T is selected based on (3.11) for a given maximum intrinsic contrast, the detection of objects will be subject to an error ϵ_2, as given by

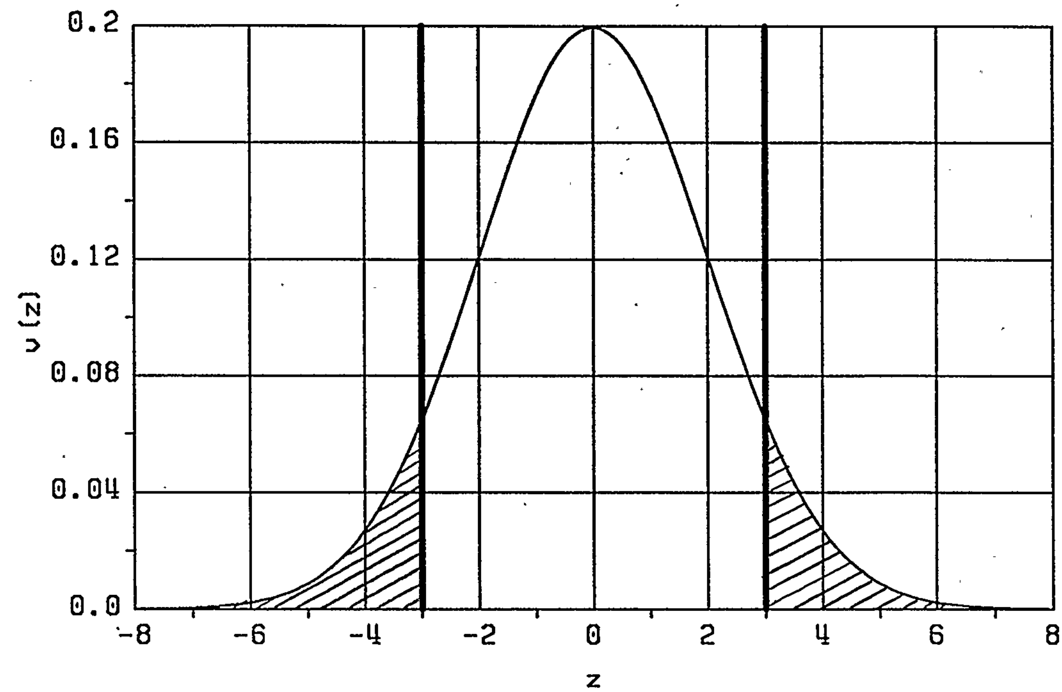

Figure 3-2 Illustration of ϵ_1 (the shaded area) associated with criterion (A) for the case mT = 3 and $\sigma = 2$

TABLE 3-1 Numerical values of ϵ_1 and ϵ_2 as functions of mT/σ and N

mT/σ	1.0	1.5	2.0	2.5	3.0	3.5	4.0
ϵ_1	0.317	0.134	0.04	0.012	0.003	0.0005	0.0001
ϵ_2 @ N=20	0.9995	0.9995	0.61	0.22	0.058	0.01	0.002
ϵ_2 @ N=50	1.0	0.9992	0.91	0.45	0.14	0.025	0.005
ϵ_2 @ N=100	1.0	1.0	0.99	0.70	0.26	0.049	0.01

(3.20). On the other hand, if ϵ_2 is given, Equation (3.20) will dictate the value of T. If c_{int_max} and ϵ_2 are both given and both are small, it may not be possible to obtain a threshold value that will satisfy (3.10) and (3.20) simultaneously. In this case, it is necessary to first apply a noise filtering operation to reduce the noise deviation. The other parameters, m and N, are fixed for a given input image and therefore are not controllable.

It can be shown that (B) is more sensitive to additive random noise than (A) because, with (B), pixels are now compared to the starting pixel rather than to the average value of the object region. The probability that the noise-corrupted value of f(P) differs from $f(P_s)$ by more than a positive value z_1 is re-written as

$$\begin{aligned} \text{prob}\,(|f(P) - f(P_s)| > z_1) &= \text{prob}\,(|f(P) - m + m - f(P_s)| > z1) \\ &= \text{prob}\,(|z + m - f(P_s)| > z_1). \end{aligned}$$

$f(P_s)$ can be greater or smaller than m. In the following calculation, it is assumed that $f(P_s)$ is greater than m; similar calculation can be carried out for the other case.

$$\text{prob}\,(|f(P) - f(P_s)| > z_1) = \text{prob}\,(|z - (f(P_s) - m)| > z1)$$

$$\text{prob}\,(|f(P) - f(P_s)| > z_1) = \text{prob}\,(z < f(P_s) - m - z_1) + \text{prob}\,(z > f(P_s) - m + z_1)$$

$$= \int_{-\infty}^{f(P_s)-m-z_1} v(z)\,dz + \int_{f(P_s)-m+z_1}^{+\infty} v(z)\,dz. \qquad (3.22)$$

The result in (3.22) is used to calculate the probability of the object pixel P being excluded from the object region:

$$\epsilon_1 = \text{prob}\,(|f(P) - f(P_s)| > mT)$$

$$= \int_{-\infty}^{f(P_s)-m-mT} v(z)\,dz + \int_{f(P_s)-m+mT}^{+\infty} v(z)\,dz. \qquad (3.23)$$

Figure 3-3 illustrates error ϵ_1 for the case $z_1 = mT = 3$, $f(P_s) - m = 2$, and $\sigma = 2$. From (3.23), ϵ_1 is equal to

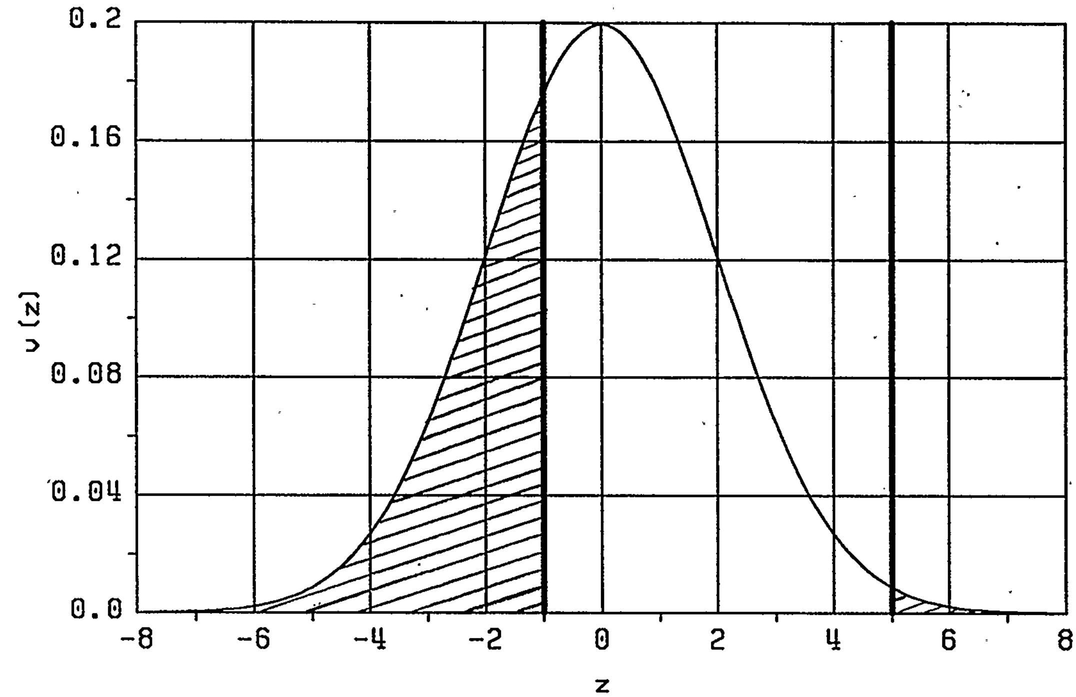

Figure 3-3 Illustration of ϵ_1 (the shaded area) associated with criterion (B) for the case $f(P_s)$ - $m = 2$, $mT = 3$, and $\sigma = 2$

$$\epsilon_1 = \int_{-\infty}^{-1} v(z)\, dz + \int_{5}^{+\infty} v(z)\, dz,$$

which is shown as the shaded area. Two observations can be made from the illustrations in Figures 3-2 and 3-3. First, ϵ_1 increases as $f(P_s)$ departs from m. Secondly, if $f(P_s)$ is equal to m, ϵ_1 is the same for both criteria (A) and (B). This means that in general ϵ_1 is higher for (B) than for (A). In other words, (B) is more sensitive to noise than (A).

Based on the foregoing analysis, the rules for selecting the criterion for various conditions are summarized below.

1. If the image is noise-free and does not contain low-contrast, blurred-boundary objects, either (A) or (B) may be used.

2. If the image is noise-free and contains low-contrast, blurred-boundary objects, (B) should be used to increase the effectiveness of the algorithm.

3. If the image is noisy and does not contain low-contrast, blurred-boundary objects, (A) should be used. If the distortion of objects is not acceptable, a noise filtering must be applied prior to contrast enhancement.

4. If the image is noisy and contains low-contrast, blurred-boundary objects, (B) must be used and a noise filtering operation must be

applied prior to contrast enhancement.

Conditions on object size

Under the influence of noise, objects tend to be broken down into smaller ones. To reduce noise amplification, one can impose a lower limit on the object area. If the object area is smaller than the lower limit, it will not be considered as a true object and will not be enhanced. The condition for enhancement is

$$oa > oa_{min} \tag{3.24}$$

where oa is the object area, and oa_{min} is the minimum allowed object area.

Since region growing is started from every pixel location, object pixels and background pixels alike, a problem arises as to whether the grown region should be considered as object or background. Usually, the background regions spread over large areas in the image. If one attempts to grow an object region from a background pixel, the grown region will be very large. Therefore, it is useful to define a maximum object area above which the region will be considered as background. This also saves processing time as the region growing process stops when the region reaches the maximum area. The maximum object area should be chosen accordingly to cover the largest object present in the image. A necessary condition for accepting an object is thus

$$oa < oa_{max} \tag{3.25}$$

where oa_{max} is the maximum allowed object area. The condition (3.25) acts as another stopping condition for the region-growing process besides the inclusion criterion. By combining (3.24) and (3.25), the enhancement condition based on object size becomes

$$oa_{min} < oa < oa_{max}. \tag{3.26}$$

3.4.2 Pixel-Grouping Techniques for Object Regions

In the preceding section, it was mentioned that pixel aggregation and split-and-merge techniques are two possible pixel-grouping methods. The technique can only be used if it is suitable to the chosen region-growing criterion. The suitability of the techniques to both region-growing criteria (A) and (B) is examined below.

- The pixel aggregation technique is ideal for (B), whereas the split-and-merge technique is not suitable to (B). The split-and-merge technique, which is region-based, can identify regions and their properties, but it cannot be related to a specific pixel such as the seed pixel P_s as required by (B).

- Both techniques are suitable to (A), even though the split-and-merge technique is a better choice. In pixel aggregation, at the start of the region-growing process, the object is small and, as a result, the average value of the object is estimated from a small sample of pixels and is thus not accurate. The split-and-merge technique starts from larger regions and therefore gives more accurate estimates for the average values of the objects.

The implementation of the split-and-merge technique is beyond the scope of this thesis. The implementation of the pixel-aggregation technique is described next.

Pixel-aggregation technique

The pixel aggregation technique can be used to grow object regions based on the uniformity criteria (A) or (B). Starting from the pixel being processed as a seed, the algorithm examines the neighboring pixels and selectively includes the pixels into the object region based on (A) or (B). If (A) is used, the average gray level of the region is updated after the inclusion of each new pixel. The same process is repeated for each of four- or eight-connected neighboring pixels of the currently grown region until no more pixels can be included. The growing process involves both spatial connectivity and pixel values.

The pixel aggregation technique can be implemented elegantly in a compact form by the use of a recursive function. A typical implementation is shown below. The function, called *expand_object*, has the task of growing the object existing at location (i1, j1) by examining the intermediate pixel P(i, j) which is 8-connected to the currently grown region.

```
expand_object (i, j, i1, j1)
    if oa < oamax and P(i, j) satisfies the chosen inclusion criterion ((A) or (B))
        mark P(i, j) as object pixel
        increment oa
        update m if (A) is used
        if (i-1 is valid) expand_object(i-1, j, i1, j1)
        if (i+1 is valid) expand_object(i+1, j, i1, j1)
        if (j-1 is valid) expand_object(i, j-1, i1, j1)
```

```
        if (j+1 is valid) expand_object(i, j+1, i1, j1)
        if (i-1 and j-1 are valid) expand_object(i-1, j-1, i1, j1)
        if (i+1 and j-1 are valid) expand_object(i+1, j-1, i1, j1)
        if (i-1 and j+1 are valid) expand_object(i-1, j+1, i1, j1)
        if (i+1 and j+1 are valid) expand_object(i+1, j+1, i1, j1)
    else
        mark P(i, j) as boundary pixel
    end if
end expand_object
```

For 4-connected objects, the last four if-statements are omitted. Before the function is called, the parameters oa and m are initialized to 0. If the recursive feature is not allowed by the chosen computer programming language, it can be realized by using "stack" or "queue" data structure [25, 27]. If oa_{max} is too large, the computer may encounter the stack overflow problem. Again, this problem can be avoided by using the stack or queue implementation.

3.5 BACKGROUND-REGION GROWING TECHNIQUES

After an object region is defined, the next step is to find the immediate background of the object. This step is needed to determine the average background gray level, which is required for determining the object contrast. To obtain the best background representation, *the background region is chosen as a layer of constant width surrounding the object boundary.* It was found experimentally that a width of 2 to 4 pixels would sufficiently present the background for human eyes. A larger width would make contrast a global measure and destroy the advantages of local adaptation. Similar to object region growing, the pixel aggregation method can be used here to grow background regions, but the inclusion criterion for the background is based only on the connectivity of pixels and not on the pixel values.

An algorithm to grow the background region, called *expand_background,* is described next. The algorithm starts from the boundary pixels that were identified by the expand_object function described in Section 3.4.2. For convenience, the boundary pixels are referred to as layer-0 background pixels. The function adds layers of pixels to the background region, one layer at a time; pixels of layer w are those that do not belong to the object and are 8-connected to those in layer (w-1). If 4-connectivity is used, the last 4 if-statements are omitted. The total number of layers is equal to the chosen background width, *bg_width*. The pseudocode of the algorithm is described below.

```
expand_background
    undo the marking for all previously marked background pixels
    for w from 1 to bg_width
        for each background pixel P(i, j) of layer (w-1)
            if (i-1 is valid and P(i-1, j) is not marked)
                mark P(i-1, j) as layer-w background pixel
            if (i+1 is valid and P(i+1, j) is not marked)
                mark P(i+1, j) as layer-w background pixel
            if (j-1 is valid and P(i, j-1) is not marked)
                mark P(i, j-1) as layer-w background pixel
            if (j+1 is valid and P(i, j+1) is not marked)
                mark P(i, j+1) as layer-w background pixel
            if (i-1 and j-1 are valid and P(i-1, j-1) is not marked)
                mark P(i-1, j-1) as layer-w background pixel
            if (i+1 and j-1 are valid and P(i+1, j-1) is not marked)
                mark P(i+1, j-1) as layer-w background pixel
            if (i-1 and j+1 are valid and P(i-1, j+1) is not marked)
                mark P(i-1, j+1) as layer-w background pixel
            if (i+1 and j+1 are valid and P(i+1, j+1) is not marked)
```

```
        mark P(i+1, j+1) as layer-w background pixel
    end for each layer
    increment w
  end for w
end expand_background
```

Figure 3-4 illustrates three examples of 2-pixel wide, 8-connected background regions for various shapes of objects, using the above algorithm. The background pixels usually surround the object as seen in all three examples in Figure 3-4, but the object may also surround background pixels as seen in the right-most example.

3.6 SUMMARY

In this chapter, a number of important concepts has been defined including connectivity, brightness uniformity, regions, and objects. Based on the foundation of the contrast model developed in Chapter 2, two object-region growing criteria, (A) and (B), were established, and their effectiveness and usefulness were compared. Two pixel-grouping techniques applicable to the region-growing criteria were discussed, namely the pixel-aggregation and split-and-merge techniques, but only the implementation of the first one was

Notation: #: object pixels, - : background pixels, .: others

```
................      ................      ................
................      ................      .....------.....
................      ................      ....--------....
.....-----......      .....-----......      ...----##----...
.....------.....      .....-----......      ..----#--#----..
.....-#----.....      .....-#-------..      ..---#----#--...
.....-##---.....      .....-#-------..      ..-#------#--...
.....-##---.....      .....-#####---..      ..-#------#--...
.....---#--.....      .....-#-------..      ..---#---#---...
.....------.....      .....-#-------..      ..----###----...
......-----.....      .....-----......      ...---------....
................      .....-----......      ....-------.....
................      ................      ................
```

Figure 3-4 Examples of background regions

examined in detail. Finally, the selection of a representative background for each object was covered. The topics that are omitted in this chapter but deserve further attention are the development of the split-and-merge technique for contrast enhancement application, and possible improvements in the case of noisy images.

Chapter 4

OBJECT-BASED CONTRAST ENHANCEMENT

This chapter discusses the processing steps involved in the object-based contrast enhancement operation after the object and background regions are defined. The first three sections describe the computation of background values, original and enhanced contrast values, and output pixel values, respectively. The dynamic range of the output image is an important issue and covered in a separate section. The properties of the contrast functions and a synthesis approach to the design of the contrast function are also examined.

4.1 BACKGROUND VALUES AND BACKGROUND CONDITIONS FOR ENHANCEMENT

In the object contrast definition (2.6), a condition on the uniformity of the background was assumed. In real images, this is not always the case. For a widely-varying background, the object contrast becomes ambiguous, and contrast enhancement is not possible. On the other hand, if the background is fairly uniform, it is possible to define the object contrast based on a representative background value which could be taken to be the mean or median of the background region. In this case, the object contrast definition (2.6) becomes

$$c = \frac{|\, f(P_{ob}) - \mu_{bg}(f(P_{ob}))\,|}{f(P_{ob}) + \mu_{bg}(f(P_{ob}))}, \tag{4.1}$$

where $\mu_{bg}(f(P_{ob}))$ is either the mean or median of the background region corresponding to the object region grown from pixel P_{ob} in image $f(P)$.

The uniformity of the background at pixel P_{ob} can be represented by the ratio of the standard deviation, $\sigma_{bg}(f(P_{ob}))$, to the mean or median of the background, $\mu_{bg}(f(P_{ob}))$. For object contrast enhancement, this ratio must be less than the allowed maximum background fluctuation, bf_{max}, i.e.,

$$\frac{\sigma_{bg}(f(P_{ob}))}{\mu_{bg}(f(P_{ob}))} \leq bf_{max}. \tag{4.2}$$

Equation (4.2) is the background uniformity condition for enhancement.

4.2 COMPUTATION OF ORIGINAL AND ENHANCED OBJECT CONTRAST

The computation of object contrast varies slightly depending on the region-growing criterion used. If (A) is used, the object contrast corresponding to pixel P_s is

$$c = \frac{|\mu_{ob}(f(P_{ob})) - \mu_{bg}(f(P_{ob}))|}{\mu_{ob}(f(P_{ob})) + \mu_{bg}(f(P_{ob}))}, \tag{4.3}$$

where $\mu_{ob}(f(P_{ob}))$ denotes the average value of the object region at pixel P_{ob} in the image f(P). If (B) is used, the object contrast becomes

$$c = \frac{|f(P_s) - \mu_{bg}(f(P_s))|}{f(P_s) + \mu_{bg}(f(P_s))}. \tag{4.4}$$

After the input object contrast is determined, the output contrast can be readily computed through a contrast function h(c):

$$c' = h(c), \tag{4.5}$$

where c and c' are the original and enhanced contrast respectively.

The contrast function only applies to "true" objects, i.e. with sizes within the predetermined limits described in (3.26). The grown region will be considered as noise if it is too small, and as part of the background if it is too large. In both cases, the object brightness remains the same under the enhancement operation.

4.3 COMPUTATION OF OUTPUT PIXEL VALUES

With respect to the output image g(P), the new enhanced contrast c' is expressed as

$$c' = h(c) = \frac{|\, g(P_{ob}) - \mu_{bg}(g(P_{ob}))\,|}{g(P_{ob}) + \mu_{bg}(g(P_{ob}))}, \tag{4.6}$$

where $g(P_{ob})$ and $\mu_{bg}(g(P_{ob}))$ are respectively the object pixel value and the mean (or median) of the background region at pixel P_{ob} in the output image g(P). If c' and $\mu_{bg}(g(P_{ob}))$ are known, $g(P_{ob})$ can be computed from (4.6). Unfortunately, $\mu_{bg}(g(P_{ob}))$ is not always known. There are two possible cases:

Case 1: The background pixels are left unchanged under the enhancement operation. This occurs when the background does not contains any parts of other enhanced objects. In this case, $\mu_{bg}(f(P_{ob})) = \mu_{bg}(g(P_{ob}))$. Equation (4.6) becomes

$$c' = h(c) = \frac{|\, g(P_{ob}) - \mu_{bg}(f(P_{ob}))\,|}{g(P_{ob}) + \mu_{bg}(f(P_{ob}))}\,. \tag{4.7}$$

With both c' and $\mu_{bg}(f(P_{ob}))$ known, $g(P_{ob})$ can be computed from (4.7):

$$g(P_{ob}) = \frac{\mu_{bg}(f(P_{ob}))\,(1 + c')}{1 - c'} \quad \text{if } f(P_{ob}) \geq \mu_{bg}(f(P_{ob})), \tag{4.8a}$$

$$g(P_{ob}) = \frac{\mu_{bg}(f(P_{ob}))\,(1 - c')}{1 + c'} \quad \text{if } f(P_{ob}) \leq \mu_{bg}(f(P_{ob})). \tag{4.8b}$$

Case 2: If the background region contains parts of other objects and if the pixels in these objects are changed under the enhancement operation, then $\mu_{bg}(g(P_{ob})) \neq \mu_{bg}(f(P_{ob}))$. In this case, $\mu_{bg}(g(P_{ob}))$ is not known and it is not possible to compute $g(P_{ob})$ based on (4.6). To resolve this problem, $g(P_{ob})$ is estimated in two or more steps:

Step 1: $\mu_{bg}(g(P_{ob}))$ is assumed to be equal to $\mu_{bg}(f(P_{ob}))$, and $g(P_{ob})$ is estimated using (4.8). With this approximation, the enhanced contrast in the output image might be less than the predetermined value. The output image obtained in this manner is considered as an intermediate result which will be processed further in the next step. The desirable contrast values are kept as the targets for all steps.

Step 2: The output image obtained from step 1 is subjected to a second contrast enhancement operation. In this operation, the object is re-constructed based on the *original* input image. This is necessary to ensure that the constructed objects are identical to the ones in step 1 for all pixels. The contrast for each object is computed, compared with the predetermined value, and increased accordingly, if necessary, toward the target value. Step 2 is repeated until all objects obtain equal or better contrast than their target values.

The iterative processing method described above will also account for changes of background values in the case of "nested" objects, i.e., objects located within others. In this situation, an outer object will form the background for the inner one. If the outer pixel values are changed in a direction to reduce the contrast of the inner object, the second iterative processing will detect this influence and adjust the inner pixel values to achieve the desirable contrast.

Reducing processing time

The number of required iterations can be reduced if a relaxed stopping condition is set up to terminate the process whenever the contrast values are found to be close to the target values within a certain tolerance for a certain percentage of objects. To further reduce the processing time, once an object region is grown, the output values for a number of pixels of the object region are calculated. This reduces the overall number of region-growing operations. If the criterion (A) is used, all pixels in the region can be processed at the same time, whereas if (B) is used, only pixels of values equal to $f(P_s)$ can be processed. If the object size falls beyond the allowable range, the object pixels remain unchanged, and all of them can be processed at the same time.

4.4 CONDITIONS FOR CONTRAST FUNCTIONS

This section discusses the conditions that a contrast function must satisfy to ensure proper enhancement. First, the contrast function must map the input contrast in the [0,1] range to the output contrast in the same range, i.e.,

$$0 \leq h(c) \leq 1, \quad \text{for} \quad 0 \leq c \leq 1. \tag{4.9}$$

Secondly, for contrast enhancement, the contrast function must satisfy

$$h(c) \geq c, \quad \text{for} \quad 0 \leq c \leq 1. \tag{4.10}$$

Thirdly, the contrast function should not enhance the internal gray level fluctuations within any object. Since the contrast corresponding to internal fluctuations is smaller than T, as shown in (3.11), the corresponding condition for the contrast function is

$$h(c) = c, \quad \text{for } c \leq T. \tag{4.11}$$

The criteria (4.9) to (4.11) form the minimum set of conditions for the contrast function. A direct result of the above conditions is that if $h_1(c)$ and $h_2(c)$ are two valid contrast functions satisfying (4.9) to (4.11), their weighted linear combination $\alpha\, h_1(c) + (1-\alpha)\, h_2(c)$, $0 \leq \alpha \leq 1$, is also a valid contrast function. This result will be used later in the next section.

Besides the above conditions, there are other practical considerations that need to be dealt with to ensure the effectiveness of the enhancement operation. One such consideration is the dynamic range, i.e., the pixel value range of the output image. The next section discusses how the dynamic range can be controlled to increase the effectiveness of the enhancement operation.

4.5 DYNAMIC RANGE CONSIDERATION

Dynamic range is an important issue that one must consider in evaluating the effectiveness of contrast enhancement techniques. Dynamic range expansion has the effect of increasing the contrast; however, if the output range goes beyond the available range of the display equipment, clipping will occur. If this is the case, the output image must be scaled back to the display range by applying gray level compression, which, as shown in Section 2.2.2, will reduce the contrast. For a meaningful comparison of contrast enhancement techniques, the original and enhanced images must be scaled to the same range.

The contrast gain of the gray level compression or stretching was expressed in (2.12). If the contrast gain is close to unity, and $f(P_{ob}) \cong f(P_{bg})$, (2.12) can be written as

$$g_c \cong 1 - ((out_{min} / k) - in_{min}) / f(P_{ob}) \qquad (4.12)$$

where k is expressed in (2.9). For compression, the contrast gain is less than unity. Equation (4.12) shows that objects of higher gray levels are less affected by compression. For bright objects, the contrast increase obtained from the object-based enhancement operation usually outweighs the contrast decrease caused by compression, so that the combined effect of the two operations is a net contrast increase. For dark objects, the net change could be an increase or decrease. For objects whose contrast values are unchanged under the object-based enhancement operation, the net change is a decrease. Furthermore, if most objects in the image are unchanged, the overall contrast of the image will be reduced. In general, the dynamic range expansion needs to be curtailed to a reasonable level to ensure that the final contrast change is an increase for the enhanced objects, and the overall contrast of the image is not severely degraded. This need is especially true for images that contain objects in the lower end of the gray scale.

To suppress dynamic range expansion, unnecessary enhancement operations (such as those for high-contrast objects) that result directly in output values exceeding the desirable range should be avoided. Unnecessary enhancement that does not directly cause dynamic range expansion can still do so indirectly as in the case of objects whose backgrounds contain parts of other objects. This is illustrated in Figure 4-1, which shows an object A whose background contains part of object B. Changing B value will cause the background value of A to change, and this necessitates a re-adjustment of A value if the enhanced contrast of A is to be kept the same as in the case of not changing B value. The re-adjustment of A value may result in dynamic range expansion. This means that if B already has high contrast, its value should be kept unchanged to prevent possible dynamic range expansion. To summarize, all unnecessary enhancement operations should be avoided in order to reduce dynamic range expansion.

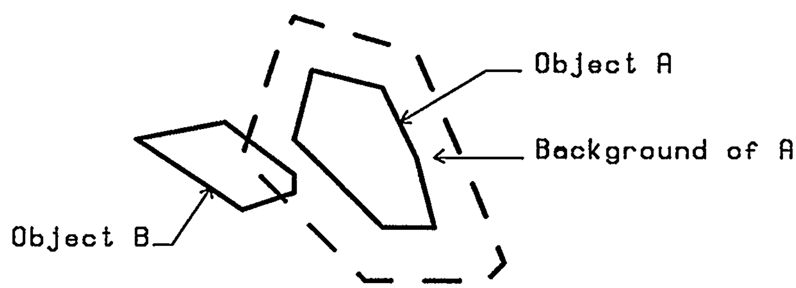

Figure 4-1 Illustration of a background containing part of another object

To avoid unnecessary enhancement, the contrast function should have a contrast enhancement regulation effect, i.e., it should provide high gain for low contrast and low gain for high contrast. The slope of the function should be steep in the low-contrast range and become less so as the contrast increases. Furthermore, as the input contrast approaches a certain maximum value, c_{max}, the output contrast should be kept the same as the original contrast, i.e.,

$$h(c) = c \quad \text{if } c \geq c_{max}. \tag{4.13}$$

If the contrast of an object is in the low range and if the corresponding output pixel value falls beyond the available range, contrast enhancement is still needed at the expense of dynamic range expansion. In this case, to suppress the range expansion while still achieving enhancement, the contrast gain can be made adaptive to the amount by which the output value extends beyond the available range. The larger the extent, the smaller the contrast gain should be. To implement this feature, a combination of two contrast functions could be used with one function producing strong enhancement and the other producing weaker effect. The net output contrast will be a linearly weighted combination of the two contrast values produced by the functions:

$$c_{out} = \alpha\, h'(c) + (1 - \alpha)\, h(c), \tag{4.14}$$

where c_{out} is the output contrast, $h(c)$ and $h'(c)$ are the strong and weak contrast functions respectively, and α is some increasing function of the relative difference β of the output pixel value with respect to the extrema of the available range. As β increases, α also increases, causing the combined contrast to be weighted toward the weak function. β can be expressed as follows:

$$\beta = \frac{p_{st} - avail_{max}}{avail_{max}} \quad \text{if } p_{st} > avail_{max}, \tag{4.15a}$$

$$\beta = \frac{avail_{min} - p_{st}}{avail_{min}} \quad \text{if } p_{st} < avail_{min}, \tag{4.15b}$$

$$\beta = 0 \quad \text{if } avail_{min} \leq p_{st} \leq avail_{max}, \tag{4.15c}$$

where p_{st} is the output value corresponding to the strong contrast function, and $avail_{min}$ and $avail_{max}$ are the minimum and maximum of the available range, respectively. The available range could be the input range or the display range. Three potential cases arise as follows:

1. $\beta = 0$: $avail_{min} \leq p_{st} \leq avail_{max}$. The strong function should be used since the output range does not stretch beyond the available range in this case. Hence $c_{out} = h(c)$. From (4.14), $\alpha = 0$.

2. $\beta = \beta_{max}$: β_{max} is the maximum possible value of β, for the strong contrast function. In this case, the weak function should replace the contrast function entirely. Hence $c_{out} = h'(c)$. From (4.14), $\alpha = 1$.

3. $0 \leq \beta \leq \beta_{max}$: In this case, α is a function of β. If a linear function is chosen for α as

$$\alpha = a\,\beta + b, \tag{4.16}$$

then a and b can be solved by using the two initial conditions for α in the first two cases: (1) $\alpha = 0$ if $\beta = 0$, and (2) $\alpha = 1$ if $\beta = \beta_{max}$. The result is $a = 1/\beta_{max}$ and $b = 0$. The final expressions of α and c_{out} with respect to β are

$$\alpha = \beta \,/\, \beta_{max}, \tag{4.17}$$

$$c_{out} = (\,\beta/\beta_{max}\,)\ h'(c) + (1 - (\,\beta/\beta_{max}\,))\ h(c). \tag{4.18}$$

With α chosen as above, the weak contrast function represents the contrast gain limit as β approaches its maximum value. Hence, the parameter c_{max} of the weak function should be chosen properly to provide sufficient dynamic range constraint for this limiting case. If the combined contrast is not satisfactory, successive enhancement operations can be applied until a desirable image is obtained.

As mentioned earlier, the available range could be chosen to be the input range or the display range, with the input range usually smaller than the display range. If the input range is used, the dynamic range control takes effect sooner, resulting in less dynamic range expansion, but also less enhancement for objects of extreme brightness. The opposite effect holds true if the display range is used.

4.6 CONTRAST FUNCTION SYNTHESIS

In earlier attempts, simple contrast functions such as sqrt(c), 1 - exp(-3c), ln(1+3c), tanh(2c), and tanh(3c) were used [1, 8]. These functions were proposed for use with the square-shaped object approximation technique described in Chapter 2. They satisfy criteria (4.9) and (4.10); however, they result in severe dynamic range expansion. Another drawback associated with the functions expressed in simple arithmetic forms such as the above is the difficulty in obtaining the desirable enhancement regulation over the entire contrast range [0,1]. To overcome these problems, one could synthesize the contrast function in a piecewise linear fashion. Such a function could be easily tailored to satisfy all criteria (4.9) to (4.12) and to obtain the desirable enhancement regulation and dynamic range control over the entire contrast range.

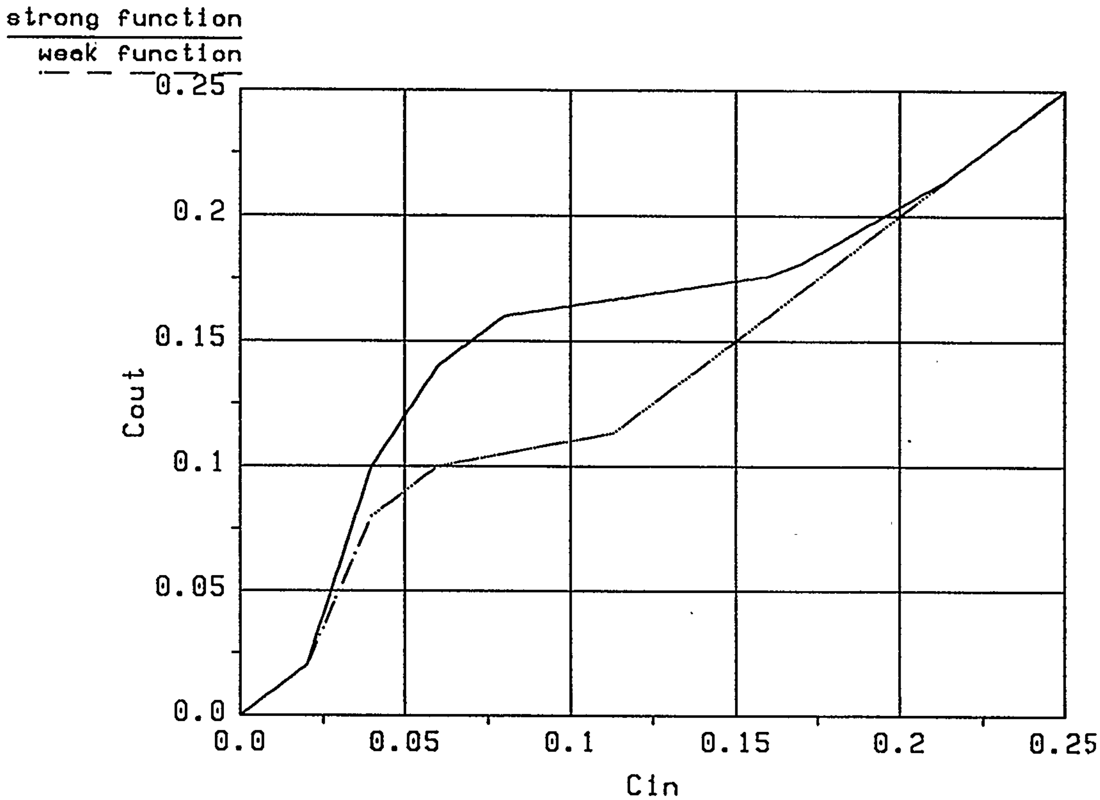

Figure 4-2 Examples of strong and weak contrast functions

Figure 4-2 shows examples of strong and weak piecewise linear contrast functions. These functions satisfy the requirements (4.9) to (4.11). The contrast ranges over which the functions produce any enhancement are: $[c_{s\_min}, c_{s\_max}]$ = [0.02, 0.215] for the strong function and $[c_{w\_min}, c_{w\_max}]$ = [0.02, 0.114] for the weak function. For each function, the lower bound is equal to the threshold T to satisfy (4.11), and the upper bound is the parameter c_{max} described in (4.13). Outside the enhancement range, the slope of the contrast function is unity. β_{max} is 0.17 and 0.085 for the strong and weak functions, respectively. Figure 4-3 shows the contrast gains for both functions.

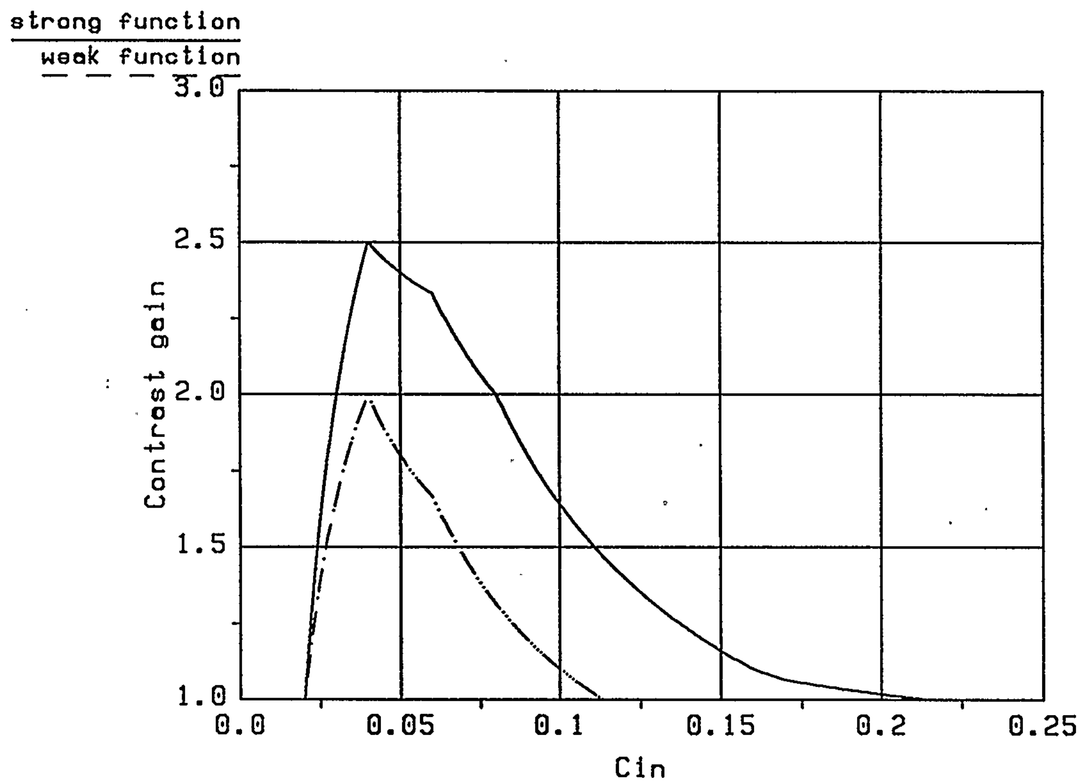

Figure 4-3 Contrast gains for the functions shown in Figure 4-2

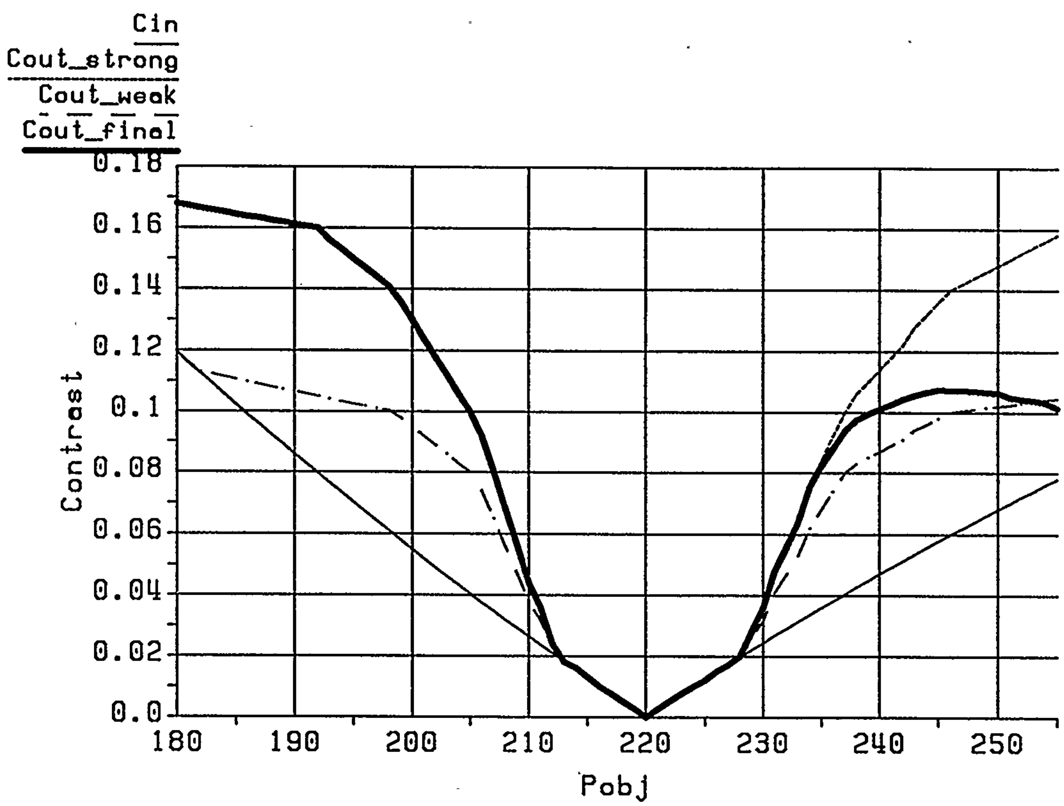

Figure 4-4 Contrast function outputs plotted against input object pixel value for the case Pbg=220

Figures 4-4 and 4-5 show the effect of combining the contrast functions as described in (4.14). Figure 4-4 plots the output contrast values obtained from the strong, weak, and the combined contrast functions against the object pixel value for a background value of 220, with $avail_{min}$ and $avail_{max}$ taken to be 1 and 255 respectively. Figure 4-5 plots the corresponding

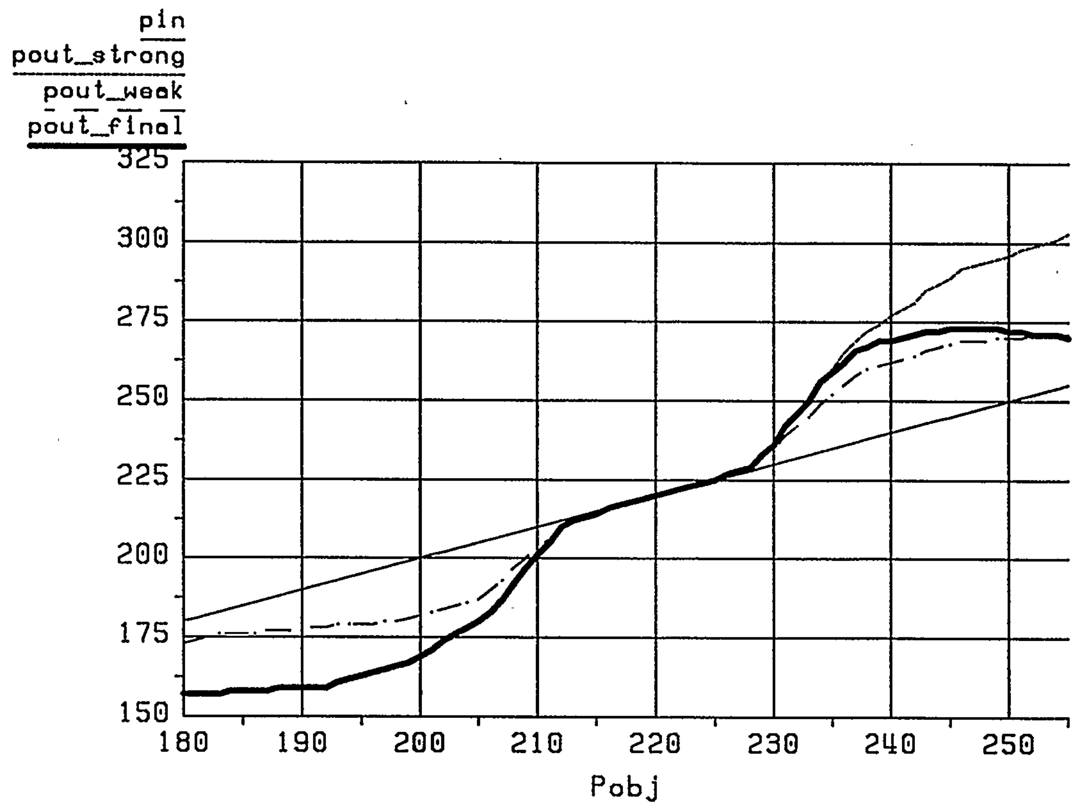

Figure 4-5 Output pixel values of contrast functions plotted against input object pixel value for the case Pbg=220

output pixel values obtained from the strong, weak, and combined contrast functions. If the output pixel value obtained from the strong function is less than 255, the combined contrast function is identical to the strong function as shown in the left-hand side portions of the curves. Otherwise, as the output value increases above 255, the contrast function is adjusted more toward the weak function (Figure 4-4), and the increase in the output value is lessened (Figure 4-5). Figure 4-4 also shows that the combined contrast curve always stays above the input contrast curve, which means that contrast enhancement is guaranteed under dynamic range control. Hence, a trade-off between contrast enhancement and dynamic range restriction has been obtained by combining the contrast functions.

4.7 SUMMARY

In this chapter, the steps involved in the object-based contrast enhancement operation were described in detail along with the explanation of the related parameters. The requirements and the synthesis of the contrast functions were discussed and illustrated with examples. A method for reducing the dynamic range expansion was presented to reduce the adverse effect on contrast caused by subsequent gray level compression. The object-based enhancement procedure involves a great deal of processing and computation; several ways of reducing the processing time were discussed, even though more research in this area may provide further improvement.

Chapter 5

RESULTS

5.1 INTRODUCTION

This chapter demonstrates the usefulness of the object-based enhancement concept and the effectiveness of the algorithms developed in the thesis. The object-based enhancement outputs for four test images are evaluated and compared with those obtained from other techniques including global stretching, global histogram equalization, and local-neighborhood unsharp masking. The local stretching and local histogram-equalized outputs are not available for comparison, but their effectiveness can be assessed based on the results obtained from their global counterparts and the theoretical evaluation discussed in Chapter 2.

The scope of the applications presented here is limited to the following conditions:

- The input image contains no noise. Although the noise influence was examined theoretically in Chapter 3, a thorough investigation requires a significant amount of work that cannot be accommodated in this thesis.

- Only the region-growing criterion (B) and the pixel aggregation technique are demonstrated, while the criterion (A) and the split-and-merge technique are not. In Chapter 3, it was shown that for no-noise applications, the criterion (B) is more effective than (A) in the detection of low-contrast, blurred-boundary objects, and that pixel aggregation is the suitable pixel grouping technique for (B). The use of (B) also implies that the effects of the brightness-adaptation level and extreme brightness conditions on contrast, as described in Chapter 2, are ignored.

The next section presents and evaluates the results, and the subsequent section provides concluding remarks.

5.2 RESULTS

This section presents four sets of results. In the first set, the input is a digitally synthesized image containing objects of varying sizes, shapes, and contrast levels. In the second set, the input image is a phantom of calcification seen in mammograms. In the third set, the input image shows a portion of a mammogram that contains clusters of calcification. Finally, in the fourth set, the input image is that of a clock taken under poor lighting conditions. The widths and heights of the input images vary from 80 to 101 pixels.

Eight-connected object and background regions are used for all images (Refer to the functions expand_object and expand_background in Chapter 3). For convenience, the same contrast functions and the same enhancement parameters are used throughout unless otherwise specified. The weak and strong contrast functions shown in Figure 4-2 are used along with the following enhancement parameters:

$T = 2\%$

$oa_{min} = 1$

$oa_{max} = 500$

$bg\_width = 2$

$bf_{max} = 20\%$

As mentioned in Section 4.5, there are two versions of object-based enhancement outputs depending on whether the available range is chosen as the input or display range. If the input range is used, the dynamic range control will be stricter at the expense of less enhancement for objects of extreme brightness. The opposite is true if the display range is used. For all output images, the display range is from 0 to 255, and the available range is chosen to be the input range unless otherwise specified. Both output versions will be shown in some cases to illustrate their differences.

To reduce the number of iterations, the condition on re-processing has been relaxed to account for only pixels whose actual contrast values are less than 90% of their targets. Most of the output images presented are processed only once, but those corresponding to a number of processing iterations are also shown in some cases to illustrate the differences.

The object-based enhancement outputs are compared against the global stretching and local-neighborhood unsharp masking outputs on the same gray level range. The unsharp masking procedure used here is operated upon a 3 x 3 neighborhood and a gain constant of 2 (Refer to (2.17)). The pixels around the borders of the unsharp masking output images are set to 0.

5.2.1 Synthesized Image

The synthesized image is shown in Figure 5-1a. It contains uniform objects of varying sizes, shapes, and contrast levels. The image size is 80 x 80, and the minimum and maximum values are 80 and 225 respectively. This image contains objects scanning a wide range of gray levels. There are two low-contrast objects of round shape present in the lower right-hand side portion of the image.

The object-based technique produces an image of gray level range from 80 to 227, i.e., with almost no dynamic range expansion. It is displayed in Figure 5-1b, after being rescaled to the input range. The contrast regulation effect is obvious throughout this image; the lower the contrast, the higher the contrast gain is. Applying the enhancement operation again to the image in Figure 5-1b results in an output with even stronger enhancement as shown in Figure 5-1c, after being scaled down to the input range from its original range of 80 to 228.

For comparison, Figure 5-1d shows the histogram-equalized image, and Figure 5-1e shows the output obtained from the local-neighborhood unsharp masking technique. Both of these figures were rescaled to the input range. While the two low-contrast objects become more visible in the object-based

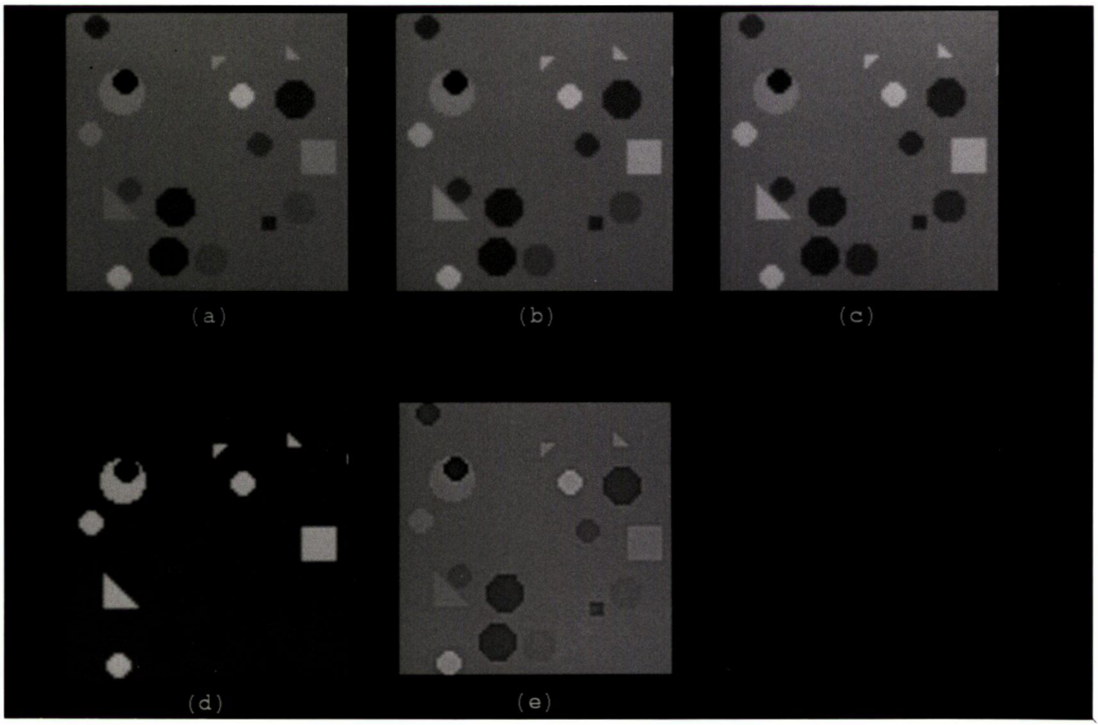

Figure 5-1 Results for the synthesized image

(a) Input image; (b) Object-based enhancement output;

(c) Result of two successive object-based enhancement operations;

(d) Histogram-equalized output; (e) Unsharp masking output.

All five images have the same gray level range.

enhancement output, they become less so in the histogram-equalized image. The unsharp masking output shows only edge enhancement in the form of bright highlights around the boundaries of the objects. For the synthesized image, the results thus have shown that the object-based technique is more effective than global stretching, global histogram equalization, and local-neighborhood unsharp masking in terms of whole-object enhancement.

5.2.2 Calcification-Phantom Image

The calcification-phantom image, shown in Figure 5-2a, contains clusters of bright small objects that represent the calcification seen in mammograms. This is a nearly binary image, with a size of 90 x 90, and minimum and maximum values of 74 and 190 respectively.

Figures 5-2b and 5-2c show the object-based enhancement outputs with the available range chosen to be the input and display range, respectively. The minimum and maximum values are 70 and 208 for Figure 5-2b, and 70 and 216 for Figure 5-2c. Using the display range has resulted in stronger enhancement for the bright spots at the expense of more dynamic range expansion.

For comparison, Figures 5-2d, 5-2e and 5-2f show the output images of global stretching, histogram equalization, and unsharp masking techniques, respectively. These images have been rescaled to the gray level range of Figure 5-2b. Compared to global stretching, the object-based enhancement technique has brought out more strongly the brightness variations in several bright clusters. The histogram-equalization output appears much brighter and enhances the brightness variations in the background, but it does not show those in the clusters (The brightness variations in the background are not enhanced by the object-based operation because their relative brightness differences are less than the threshold T). The unsharp masking output shows edge enhancement and some whole-object enhancement for very small, bright objects only.

5.2.3 Mammogram Image

The mammogram image, displayed in Figure 5-3a, shows a portion of a mammogram where calcification deposits are present in the form of small bright spots. The image size is 100 x 90, and the minimum and maximum values are 58 and 255 respectively.

Since the maximum values of the input and display range are equal, the object-based enhancement outputs are the same for both cases when the

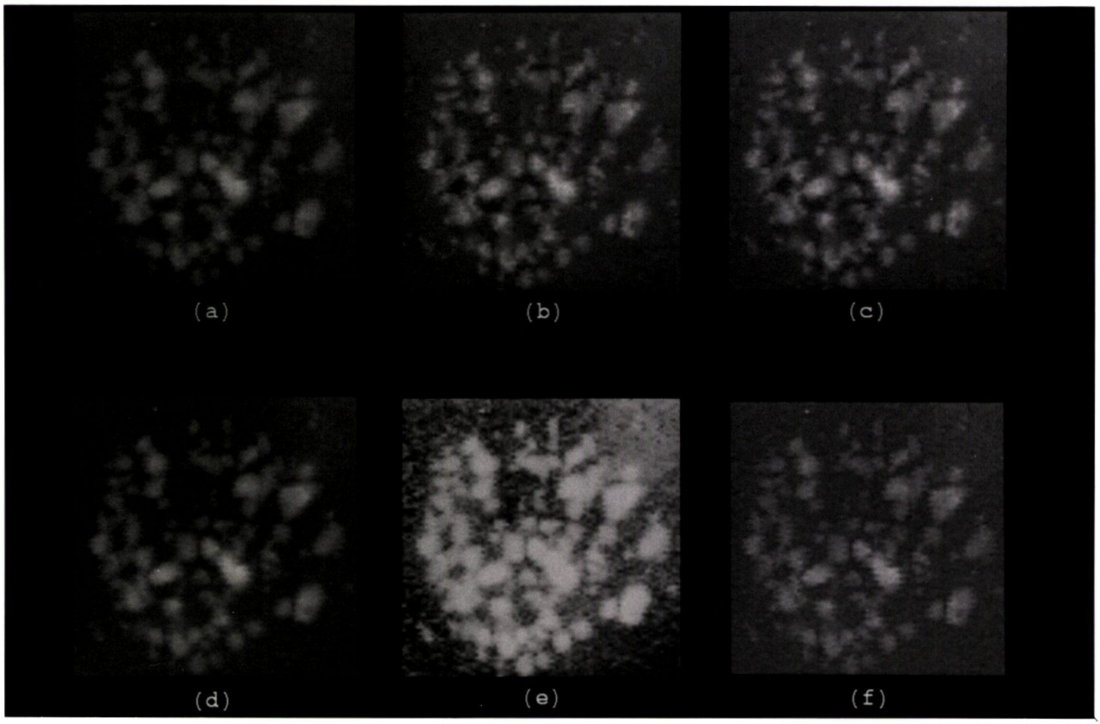

Figure 5-2 Results for the calcification-phantom image

(a) Input image; (b) and (c) Object-based enhancement outputs:

(b) with available range equal to input range,

(c) with available range equal to display range;

(d) Global stretching output; (e) Histogram-equalized output;

(f) Unsharp masking output. Figs b,d,e and f have the same gray level range.

available range is chosen to be the input or display range. The output image has a minimum and maximum value of 55 and 276 respectively, and is displayed in Figure 5-3b after being rescaled to the input range. Another output version in which dynamic range control is omitted is shown in Figure 5-3c, after being rescaled to the input range. The original minimum and maximum values for this image are 55 and 291, respectively. It is evident that the bright calcification spots have become more visible in Figures 5-3b and 5-3c. The difference in enhancement level for the bright, low-contrast objects between these two images is calculated below for typical object and background values of 240 and 220, respectively.

The enhancement obtained without dynamic range control is about 1.13 times stronger than that obtained with dynamic range control, as shown in Figure 4-4. The output image in the first case, however, is subject to more contrast loss caused by the gray level compression than the one in the latter case. The gray level compression is the linear transformation that maps the range [55, 291] to [55, 276]. The parameter k of this transformation is, based on (2.9),

$$k = (276 - 55) / (291 - 55) = 0.94.$$

The contrast gain of the gray level compression for an object value of 200 is, based on (4.12),

$$g_c = 1 - (55 / k - 55) / 200 = 0.98$$

Thus the enhancement in Figure 5-3c should be stronger than that in Figure 5-3b by 1.13 * 0.98 = 1.1 times. The differences between these two figures are not visually apparent because of subtle contrast changes. The other reason is the influence of the brightness-adaptation level that effectively reduces the perceived contrast of the brighter objects. The above calculation, however, has shown that the effects of gray level compression on contrast are negligible for bright objects, and dynamic range control can be relaxed for images containing bright objects only.

The object-based enhancement output obtained after seven processing iterations is shown in Figure 5-3d, after being rescaled to the input range. The original minimum and maximum values of this image are 55 and 303, respectively. The iterative processing affects 11% of the pixels processed in the first iteration. The improvements, however, are not visible because of further gray level compression and the effect of the adaptation-brightness level.

Figures 5-3e and 5-3f show the histogram-equalized and unsharp masking outputs respectively, after being scaled back to the input range. Figure 5-3e has a brighter appearance, while Figure 5-3f shows image sharpness improvement. Both images, however, fail to bring out the calcification features.

5.2.4 Clock Image

The clock image, shown in Figure 5-4a, was taken under poor lighting conditions. The image size is 101 x 101, and the minimum and maximum pixel values are 79 and 222 respectively. The threshold value T is chosen to be 4% to account for brightness variations intrinsic to the features present in the image. The output of a single object-based enhancement iteration is shown in Figure 5-4b, which has minimum and maximum values of 75 and 241 respectively. Features such as the numerals, the hour marks, the border of the clock, and the lines on the wall appear darker and more visible in the output image.

The result of six processing iterations is shown in Figure 5-4c, after being rescaled to the range of Figure 5-4b. The original minimum and maximum values of this image are 74 and 267, respectively. The multiple processing iterations affect 35% of the pixels processed in the first iteration. The

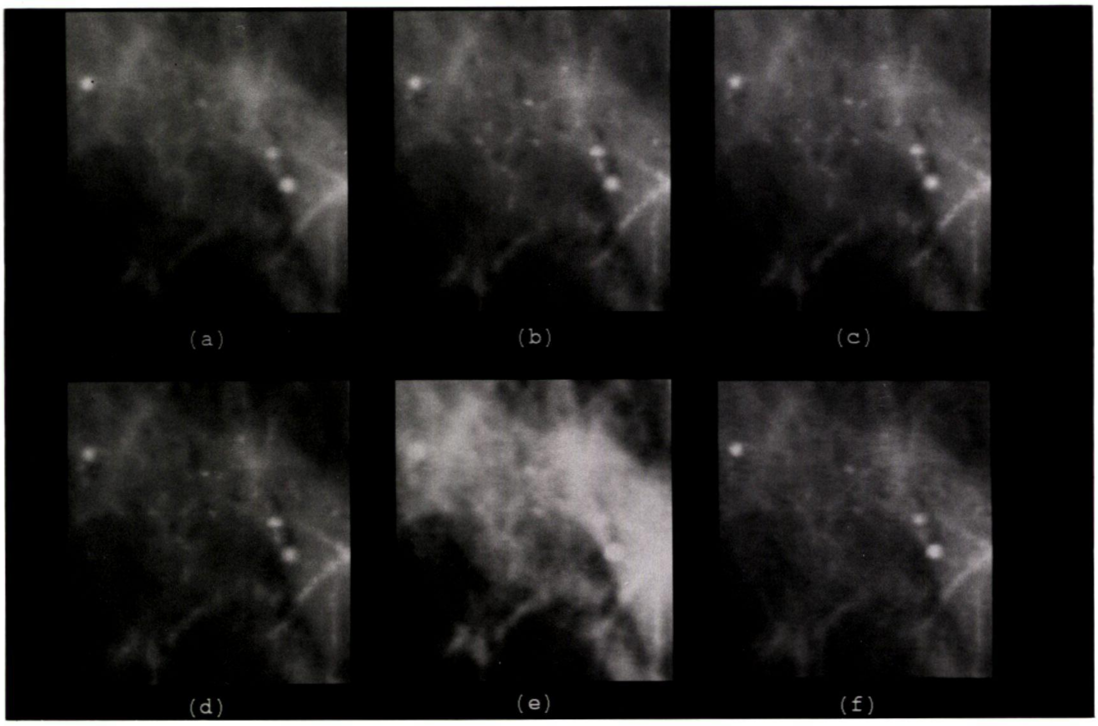

Figure 5-3 Results for the mammogram image:

(a) Input image; (b) to (d) Object-based enhancement outputs:

(b) with dynamic range suppression, (c) without dynamic range suppression,

(d) after seven iterations; (e) Histogram-equalized output;

(f) Unsharp masking output.

All outputs have been rescaled to the input range.

brightness variations in the bright area by the center of the clock become visible as a result of multiple iterations. However, the improvement on the dark features are not visible despite of a large percentage of pixels being re-processed. The reason is that the contrast changes produced by multiple processing iterations are too small to be distinguishable in this case.

Applying two successive object-based enhancement operations produces an output with stronger enhancement as shown in Figure 5-4d. The global stretching and unsharp masking outputs are shown in Figures 5-4e and 5-4f respectively. The images in Figures 5-4d to 5-4f have been rescaled to the range of Figure 5-4b for comparison. Compared to the object-based enhancement output, the global stretching output shows less enhancement, and the unsharp masking output shows feature sharpness improvement as opposed to whole-feature contrast enhancement.

5.3 CONCLUDING REMARKS

The effectiveness of the object-based enhancement technique has been demonstrated through the results of application to four images. The technique was found to be more effective, on the same output range, than global stretching, global histogram equalization, and local-neighborhood unsharp masking techniques in terms of whole-object enhancement,

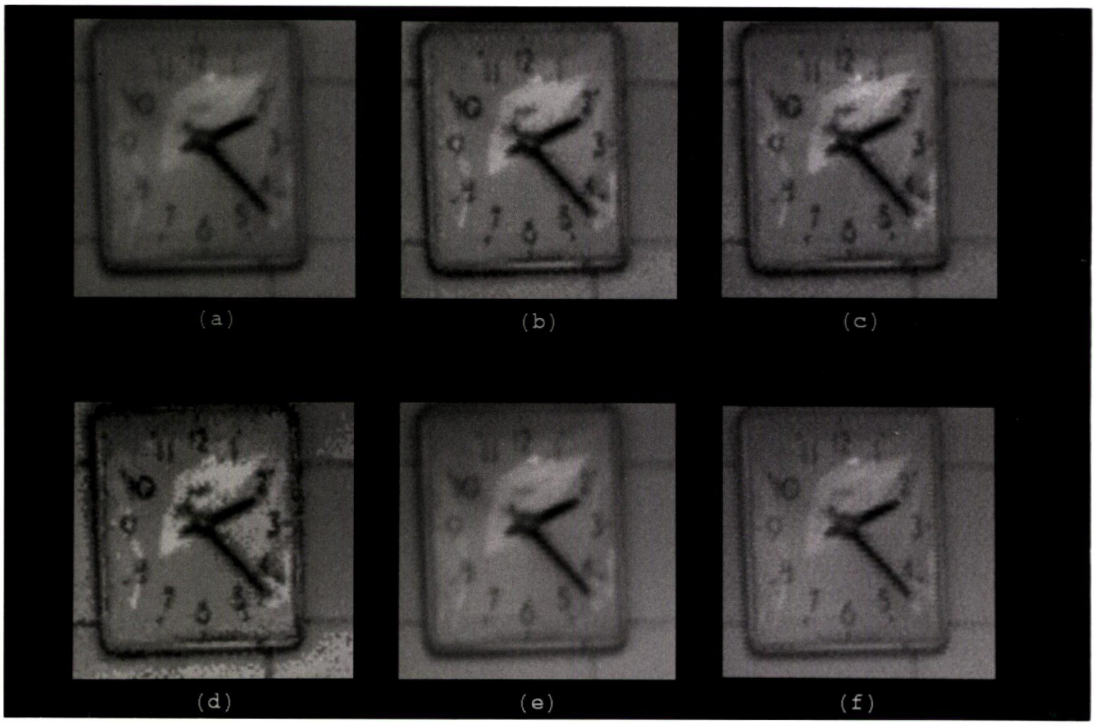

Figure 5-4: Results for the clock image

(a) Input image; (b) to (d) Object-based enhancement outputs:

(b) with one iteration, (c) with six iterations,

(d) with two successive operations; (e) Global stretching output;

(f) Unsharp masking output.

All images from b to f have the same gray level range.

especially for low-contrast objects. It provides stronger enhancement compared to gray level stretching. It enhances objects locally and regulates the level of enhancement, in contrast with histogram equalization, which provides strong overall enhancement yet does not guarantee enhancement for all objects. The object-based technique enhances objects as whole entities as opposed to edge enhancement produced by local-neighborhood unsharp masking. The local stretching and local histogram techniques provide stronger enhancement than their global counterparts, but at the same time, they generate artifacts as a result of joining sub-images together. In general, the above comparison still holds for the local stretching and histogram techniques.

The object-based enhancement technique is most useful in applications where it is desired to bring out low-contrast details at an enhancement level that is not required to be linear. An example is the processing of mammograms to bring out the presence of calcification. While only a few images are shown here, the technique could be made useful for a variety of images by adjusting the operation parameters and the contrast functions according to specific needs.

Chapter 6

CONCLUSION

6.1 CONCLUSION

This thesis has established the essential algorithms that are required for object-based contrast enhancement. Starting from a contrast model, accurate object- and background-region growing techniques were developed. An effective means was implemented to curtail the dynamic range control while still allowing enhancement. The selection of a proper contrast function is important in providing the desired level of enhancement, contrast regulation, and dynamic range control; this task has become easier due to the piecewise-linear synthesis design approach.

The effectiveness of the object-based enhancement technique was demonstrated through application to a few images. The technique was also compared with others including global stretching, global equalization, their local counterparts, and local-neighborhood unsharp masking. The comparison was done at the conceptual level and further supported by examining output images. A conclusion can be drawn that the object-based technique is the most effective in applications where it is desired to enhance objects or features, especially the low-contrast ones, as whole entities, and the enhancement level is not required to be linear. The enhancement of the clusters of calcification present in mammograms is one of such applications that would benefit from the object- based technique, as illustrated in Chapter 5. For a given application, the parameters of the object-based technique and the contrast functions can be adjusted to bring about the best results.

Several issues related to the object-based technique were encountered and yet were not explored in this thesis due to their complexity. These were identified at the end of each chapter and are summarized in the next section.

6.2 FUTURE IMPROVEMENTS

Following is a list of items that needs to be addressed to further improve the effectiveness of the object-based enhancement technique:

- To develop a full contrast model that would account for: (1) the extreme brightness conditions under which the Weber's law does not hold and the perceived brightness is no longer a linear function of the relative brightness difference, and (2) the influence of the adaptation-brightness level of human visual system on the perceived contrast. Such a model will reflect more truthfully the perceived contrast for a wide range of gray levels.

- To implement the region-growing criterion (A) using the split-and-merge technique. This region-growing scheme is suitable for noisy images.

- To thoroughly investigate the influence of random noise on the effectiveness of region-growing criteria (A) and (B), and possibly develop new criteria that would work better.

- To further reduce the processing time. The object-based enhancement operation is complicated and time-consuming, and further ways to reduce the burden of computation need to be explored.

The implementation of the above items will certainly increase the effectiveness of the technique and widen the scope of applications.

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