Automatic Extracted Object Technique for Contrast Enhancement Medical Images

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Abstract

The aim of this work is a proposed system to enhance automatically the contrast of the desired region in the medical image to get the wanted information without enhancing the contrast of the whole image.
The proposed system includes the automatic extraction process, the automatic contrast enhancement process and finally reinsertion process for region in the image.
Threshold, smoothing, boundary extraction, chain code or region filling techniques were used in the automatic extraction process. While, histogram equalization, histogram stretching, gray level grouping (GLG), fast gray level grouping (FGLG) or auto-contrast techniques were used in the automatic contrast enhancement process for an extraction region from the image. According to image appearance, GLG, FGLG and histogram stretching are the best techniques to enhance contrast in the RGB image. Auto-contrast technique lowers accuracy, while histogram equalization results are unacceptable.

Keywords: Automatic contrast enhancement, gray level grouping, fast gray level grouping, medical image, non-uniform region enhancement.

الخلاصة

إنّ هدفَ هذا العمل يُقتَرحُ نظامَ لتَحسين آلياً مقارنةِ المنطقةِ المطلوبةِ في الصورةِ الطبيةِ للحُصُول على المعلوماتِ المطلوبةِ بدون تَحسين الصورةِ الكاملةِ. يَتضمّنُ النظامُ المُقتَرَحُ عمليةُ الإنتزاعِ الآليةِ، عملية تحسينِ المقارنةِ الآليةِ وأخيراً عمليةِ إعادة إدخالِ ألمنطقةِ في الصورةِ.
العتبة أو صَقّل أو إنتزاع أو حَدِّ أو رمزِ أو سلسلةِ أو تقنياتِ منطقةِ المالِئةِ إستعملتْ في عمليةِ الإنتزاعِ الآليةِ.
بينما، مساواة مدرج إحصائي، مدرج إحصائي يَمتدُّ، تجميع مستوي رمادي (GLG تجميع مستويَ ر ماديَ السريع (FGLG) أو تقنيات مقارنةِ آليةِ إستعملتْ في عمليةِ تحسينِ الآليةِ لمنطقةِ أصلِ مِنْ الصورةِ. طبقاً لظهورِ الصورةِ، GLG، FGLG وإمْتِداد مدرج إحصائي أفضل التقنياتِ لتَحسين مقارنةِ صورةِ الآر جي بي. تقنية المقارنةِ الآليةِ تُنزّلُ دقةَ، بينما نَتائِج مساواةِ مدرج إحصائي غير مقبولة.

1. Introduction

From our appointment, unavailable technique to enhance the contrast of the desired region automatically, and contrast enhancement of the whole image is not an optimal solution to enhance the contrast of a desired region in the image. Therefore, the proposed system will be designed to solve this problem. The purpose of an image contrast enhancement method is to increase image visibility and details. Numerous enhancement methods have been proposed in the literature such as histogram processing methods [1-3] , gray level compression and stretching using exponentials and polynomials [1, 2], spatial statistical filtering [4], and frequency domain processing techniques [5]… etc. The image enhancement methods can be considered by many common factors such as enhancement efficiency, computational requirements, application suitability…etc.

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Contrast enhancement techniques can be classified into manual techniques, adaptive techniques and automatic techniques.
Automatic techniques give us an optimal level of contrast enhancement automatically depending on some conditions without adding information, such as Histogram equalization, Gray level grouping… etc [1, 6, 7]. The proposed system will be including extraction process and contrast enhancement for the desired region in medical image.

2. Global automatic image enhancement technique

Contrast enhancement techniques had wide area of importance to make the image more visually suitable and to improve the details in the image. Some techniques are very powerful in some cases and not suitable in other cases depending on the original image. Many techniques used to enhance the contrast of the image automatically, like:

2.1 Histogram Equalization.
It is a very well known technique used to enhance the contrast of the image. This technique tries to redistribute the gray level uniformly on the gray scale [1]. In principle, the histogram equalization method increases the contrast of the image by transforming its histogram into a uniform one that spans the full gray-level range. It is based on the assumption for maximum transfer of information; the perceived distribution (histogram) of gray-levels in an image should be uniform. It can be easily showed that the discrete 8-bit gray-scale images and the histogram equalization method achieve this by using the transformation function [0, 255] in eq. (1).

$$s = T(r) = 255 \times \sum_{w=0}^{r} h_i(w)dw$$
$$= 255 \times CDF(r), \quad r \in [0,255] \quad \text{... (1)}$$

Which is simply the cumulative distribution function *CDF(r)* of the normalized original image histogram $h_i(r)$ [1, 2, 6].

2.2 Histogram stretching.
This technique is used to stretch the histogram of the image along the gray scale. The histogram of the image can be modified by mapping function, which will stretch the original histogram of the image. The mapping function of this technique is represented by eq. (2).

$$J = \left[\frac{I - I_{min}}{I_{max} - I_{min}}\right][MAX - MIN] + MIN \quad \text{... (2)}$$

Where I_{min} is the smallest gray level value, I_{max} is the largest gray level value, MAX and MIN is the maximum and minimum gray level values possible (for 8-bit image these values are 0 and 255) [1].

2.3 Auto-contrast technique.
One of the newest techniques used for image contrast enhancement is auto-contrast technique, which is an automatic technique. The core idea of this technique is to redistribute the image histogram on the gray scale by using the mapping in eq. (3).

$$J = MAX \times \frac{I - I_{MIN}}{I_{MAX} - I_{MIN}} \quad \text{…. (3)}$$

Where I is the input image, I_{MIN} is the minimum gray level of the input image, I_{MAX} is the maximum gray level of the input image, and MAX represent the maximum gray level value (MAX=255 for an 8 bit image).

2.4 Gray level grouping (GLG).
It is one of the newest techniques to enhance the contrast of the image. It is fully automatic technique so it gives the optimal level of contrast enhancement.

The basic procedure grouped the histogram components of the low-contrast image into the proper number of bins according to the selected criterion, then redistributed these bins uniformly over the gray-scale, and finally ungrouped the previously grouped [7]. The algorithm of this technique is described as follow:

i. Assigned the non-zero component in the original histogram.

$$G_n(i) = H_n(k) \qquad \dots (4)$$

$$for \quad H_n(k) \neq 0$$

$$k = 0,1,2, \dots, M-1;$$
$$i = 1,2,3, \dots, n.$$

ii. Record the left and right limit, $L(i)$ and $R(i)$, of the gray-level interval represented by $G_n(i)$.

$$L_n(i) = R_n(i) = k, \quad \dots (5)$$

$$for \quad H_n(k) \neq 0$$
$$k = 0,1,2, \dots, M-1;$$
$$i = 1,2,3, \dots, n.$$

iii. The first occurring smallest $G_n(i)$ is found where

$$a = \min_i G_n(i) \qquad \dots (6)$$

And i_a is the group index corresponding to the smallest $G_n(i)$

iv. Now group the $G_n(i_a)$ is merged with the smallest of its two adjacent neighbors, and the gray-level bins $G_n(i)$ are adjusted to create a new set of bins $G_{n-1}(i)$, as follow:

$$G_{n-1}(i) = G_n(i),$$
$$for \ i = 1,2, \dots \dots, i' - 1$$
$$G_{n-1}(i) = a + b, \quad for \ i = i'$$
$$G_{n-1}(i) = G_n(i+1),$$

$$for \ i = i' + 1, i' + 2, \dots, n-1 \qquad \dots (7)$$

Where

$$b = \min\{G_n(i_a - 1), G_n(i_a + 1)\} \quad \dots (7a)$$

$$i' = \{i_a - 1, \ for \ G_n(i_a - 1) \leq G_n(i_a + 1) \qquad \dots (7b)$$

$$L_{n-1}(i) = \{L_n(i), \ for \ i = 1,2, \dots, i'$$
$$\{L_n(i+1), \ for \ i = i' + 1, i' \ 2, \dots, n-1$$

$$R_{n-1}(i) = \{R_n(i), \ for \ i = 1,2, \dots, i' - 1$$
$$\{R_n(i+1), for \ i = i', i' + 1, \dots, n-1 \qquad \dots (7c)$$

v. Calculate the number of gray levels, N_{n-1}, that each gray-level bin will occupy in the resulting image.

$$N_{n-1} = \frac{M-1}{n-1} \qquad \dots (8)$$

Where $n-1$ is the total number of bins.

To prevent that component from occupying too many gray levels let

$$N_{n-1} = \frac{M-1}{n-1-\alpha} \qquad \dots (8a)$$

Where α is a constant between (0-1).

vi. There are four cases to construct the transformation function as $T_{n-1}(k)$ follows:

If $T_{n-1}(k) \neq R_{n-1}(k)$ and the gray level k falls inside gray-level bin $G_{n-1}(i)$, there are two ways to construct the transformation function depending on both $L_{n-1}(1)$ and $R_{n-1}(1)$,

$$T_{n-1}(k) = \left(i - \alpha - \frac{R_{n-1}(i)-k}{R_{n-1}(i)-L_{n-1}(i)}\right)N_{n-1} + 1,$$

$$for\ L_{n-1}(1) = R_{n-1}(1)$$

$$T_{n-1}(k) = \left(i - \frac{R_{n-1}(i)-k}{R_{n-1}(i)-L_{n-1}(i)}\right)N_{n-1} + 1,$$

$$for\ L_{n-1}(1) \neq R_{n-1}(1) \quad \ldots (9)$$

If $L_{n-1}(1) = R_{n-1}(1)$ or the gray level k fill between $G_{n-1}(i)$ and, $G_{n-1}(i+1)$ then there are two ways to construct the transformation function depending on both $L_{n-1}(1)$ and $R_{n-1}(1)$,

$$T_{n-1}(k) = (i - \alpha)N_{n-1},$$

$$for\ L_{n-1}(1) = R_{n-1}(1)$$

$$T_{n-1}(k) = iN_{n-1},$$

$$for\ L_{n-1}(1) \neq R_{n-1}(1) \quad \ldots (10)$$

If $k \geq R_{n-1}(n-1)$, then the transformation function will be

$$T_{n-1}(k) = M - 1 \quad \ldots (11)$$

If $k \leq L_{n-1}(1)$, then the transformation function will be

$$T_{n-1}(k) = 0 \quad \ldots (12)$$

3. The Proposed System

The proposed system consists of two major parts: automatic object extraction process, automatic object contrast enhancement process and finally reinsertion process for object in the image.

The object extraction part in our proposed system is divided into two types of extraction: uniform region and non-uniform region.

The uniform region of object extraction part consists of one step only, which is defining the dimension of the sub-image in the original image as shown in figure (1).

While, the non-uniform object extraction consists of the flowing steps:

Step 1) Define the dimension of the sub-image in the original image as shown in figure (1).

Step 2) Applied threshold algorithm on the sub-image. Hard threshold can be described as the usual process for setting the coefficient to zero whose its absolute values are less or equal to the threshold value

T. Hard threshold, also called (kill/keep) strategy, is the simplest method, and can be stated as types which are:

$$g(m,n) = \begin{cases} 1 \text{ for } f(m,n) > T \\ 0 \text{ for } f(m,n) \end{cases} \quad \ldots (13)$$

Where g (m, n) is the output image, f (m, n) is the input image and T is the threshold value.

The threshold algorithm is used to separate the interested region in the sub-image from the other parts of it. To complete this step, multiply the original sub-image with the sub-image after threshold. This step can be explained in figure (2) [8].

Step 3) Bullard (smoothing) the sub-image. Apply the low-pass filter on the sub-image after threshold process. This step is very important to reduce the noisy boundary if it is exist, as shown in figure (3).

Step 4) Apply the boundary extraction and chain code algorithms on the resultant image from step 3. Boundary extraction used to extract the boundary of an object from the binary image. This means it's important to convert the sub-image to the binary form by threshold step, and then extract the boundary of that object. Boundary extraction depends on erosion operation, where the image is first eroded, and then the original image subtraction from the eroded image. The boundary extraction algorithm can be described in the eq. (14).

$$g = f - (f \ominus B) \quad \dots (14)$$

where, g is the boundary extraction result, f is the original image and B is a structure element (which is a two-dimensional, or flat, structuring elements consist of a matrix of 0's and 1's, typically much smaller than the image being processed. The center pixel of the structuring element, called the origin. The pixels in the structuring element containing 1's define the

It is important to represent the boundary by connected a sequence of straight line segments of specified length and direction. The direction of each segment is coded by using numbering scheme. The boundary owing to noise neighborhood of the structuring element). Imperfect segmentation leads to change in the code that may not necessarily be related to the shape of the boundary. The boundary resample by selecting larger grid spacing proposed to solve this problem. Depen ding on the proximity of the original boundary to the nodes, the accuracy of the resulting code representation depends on the spacing of the sampling grid. It's important to treat the code as circular sequence and redefines the starting point that the resulting sequence of numbers forms an integer of minimum magnitude to normalize the chain code with respect to the starting point. Chain code can be normalized by using the first difference of the chain code instead of the code itself. The difference is loand simply by counting (counter-clockwise) the number of directions that separate two adjacent elements of the code. The chain code algorithm was used to detect the longest boundary belonging to interested region in the sub-image, as shown in figure (4), [1, 9].

Step 5) Fill the region inside the boundary by 1's. Region filling is based on set of dilation, complement, and intersection. Firstly in image filling is to complement the original image. The secondly is the dilation processes, which can be started from point inside the region, then dilate the point with the structuring element and this process will be continue up to fill the region, as shows in figure (5).

Step 6) Multiply the resultant image from step 5 with the original sub-image to get the final object extraction step result as shows in figure (6).

For color (RGB) images, the non-uniform object extraction can be applied to each band (red, green and blue) separately, and then reconstruct

Result of the three bands to form the final sub-image.

Object contrast enhancement is the second essential part in our technique. In this part the contrast of the extracted region will be enhanced. It is important to try many techniques to satisfy the optimization level for sub-image contrast enhancing. In this part, the techniques that have been explained in section (2) will be used to enhance the extracted region contrast. Figure (7) shows a diagram of object contrast enhancement step.

The final step of the proposed technique is to reinsert a modifed sub-image.

In this step, the enhanced extracted interested region is reinserted in the original image. This step is voluntary step not an obligatory step depend on the user of this technique. Figure (8) shows the flowchart of the proposed technique.

4. Experimental Results

This technique has been tested on a color (RGB) image as shown in figure (10). We show the difference of global contrast image enhancement and the proposed technique enhancement. Figure (9) shows the original image that we have applied our technique to.

The images in figure (10) show the results of the application of our teachnique on the image shown in figure (9). While the images in figure (11) show the effect of enhancing the contrast of the whole image shown in figure (9). It is very clear how many details appeare when applying the proposed technique on the image.

5. Conclusion

The system consisting of a combination of techniques for enhancing the contrast of an interested region in the medical image, was proposed. From the results shown of the proposed system, we found;

1. Resultant images from Histogram equalization implementation have a high standard deviation. But the image appearance and the redistribution of the image histogram make the resultant images unacceptable for both grayscale and color images.
2. Resultant images from gray level grouping, FGLG and histogram stretching implementation have a high standard deviation. The image appearance and the redistribution of the image histogram make the resultant images acceptable for both grayscale and color images.
3. Resultant images from auto-contrast implementation have a high standard deviation. The image appearance and the redistribution of the image histogram for grayscale images make the resultant images acceptable, while they are unacceptable for color images.
4. However, from the bravo's points, both uniform and non-uniform extraction can be used to extract the interested region in the grayscale image with high accuracy. For color image, uniform extraction can be used to extract the interested region with high accuracy, while non-uniform extraction can’t be used with the same accuracy because the color image consists of three bands.
5. GLG technique, FGLG technique, histogram stretching have better results than other techniques.
6. Auto-contrast technique is more suitable for grayscale image enhancing than color image enhancing. While, image complement is the worst technique for image enhancement especially in color (RGB) images.
7. Automatic techniques give us the optimal results without any intervention by the proposed system users. Manual and adaptive techniques give us the

optimal results with some intervention by the proposed system users. The user can have the optimal results by trial and error.

8. Finally, contrast enhancement results of this work are better than the global contrast enhancement of the same image when using the same techniques for an interested region in the image.

6. References

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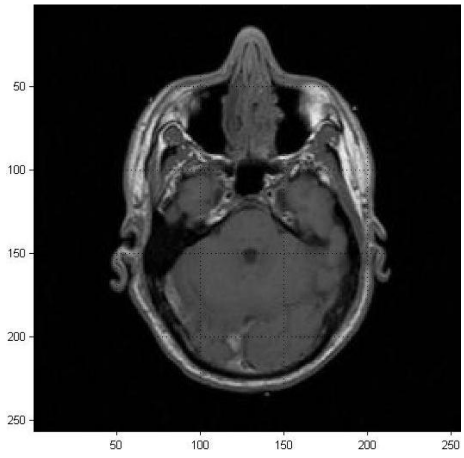
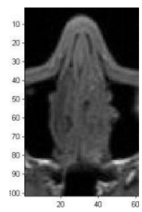
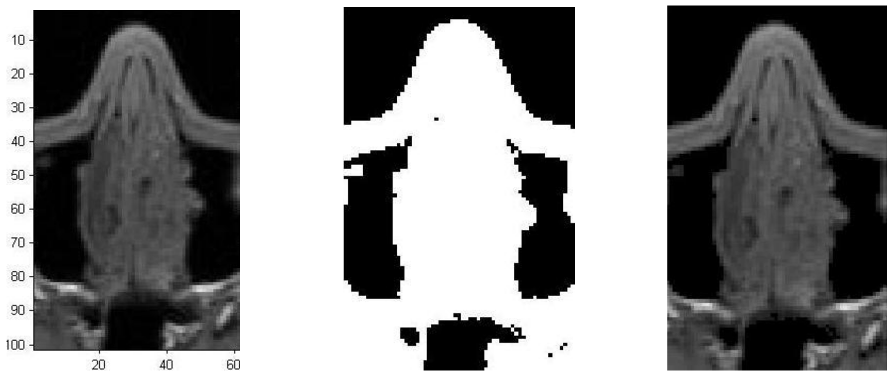




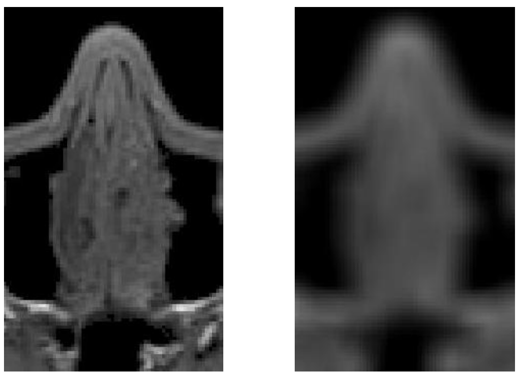
(a) Original image (b) extracted sub-image

Figure (1); Object extraction first type



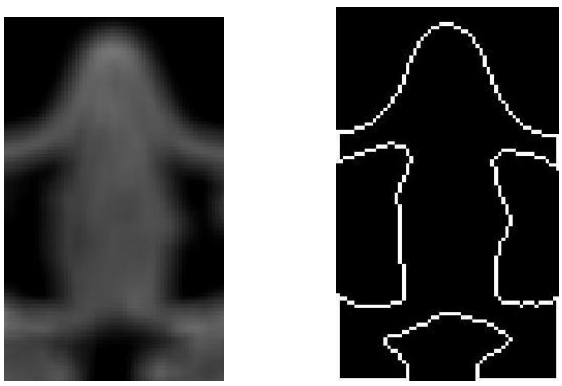
(a) Original image (b) after threshold (c) multiply (a)and(b)

Figure (2); Object extraction threshold step.



(a) Resultant second step image (b) image after smoothing

Figure (3); Object extraction smoothing step.

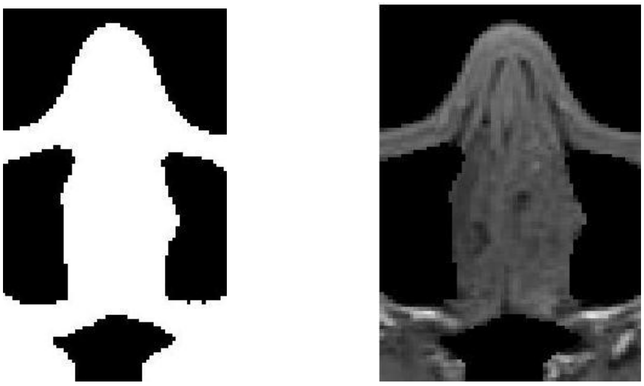


(a) Third step result (b) Fourth step result of image (a)

Figure (4); Object extraction boundary extraction step.

(a) Fourth step result (b) Fifth step result of image (a)

Figure (5); Object extraction region filling step.



(a) Fifth step result (b) Final object extraction step (6)

Figure (6); Object extraction step final result.

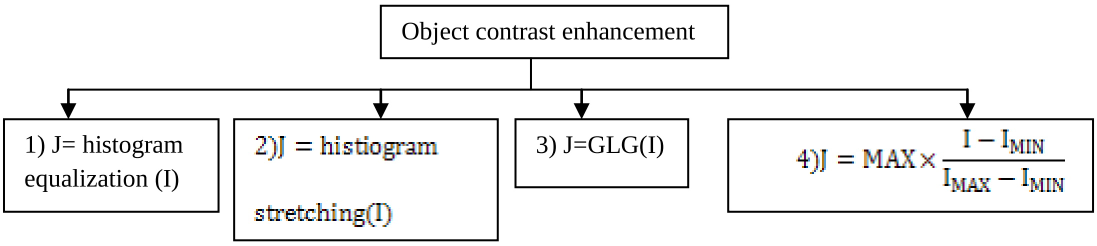


Figure (7); Object contrast enhancement diagram

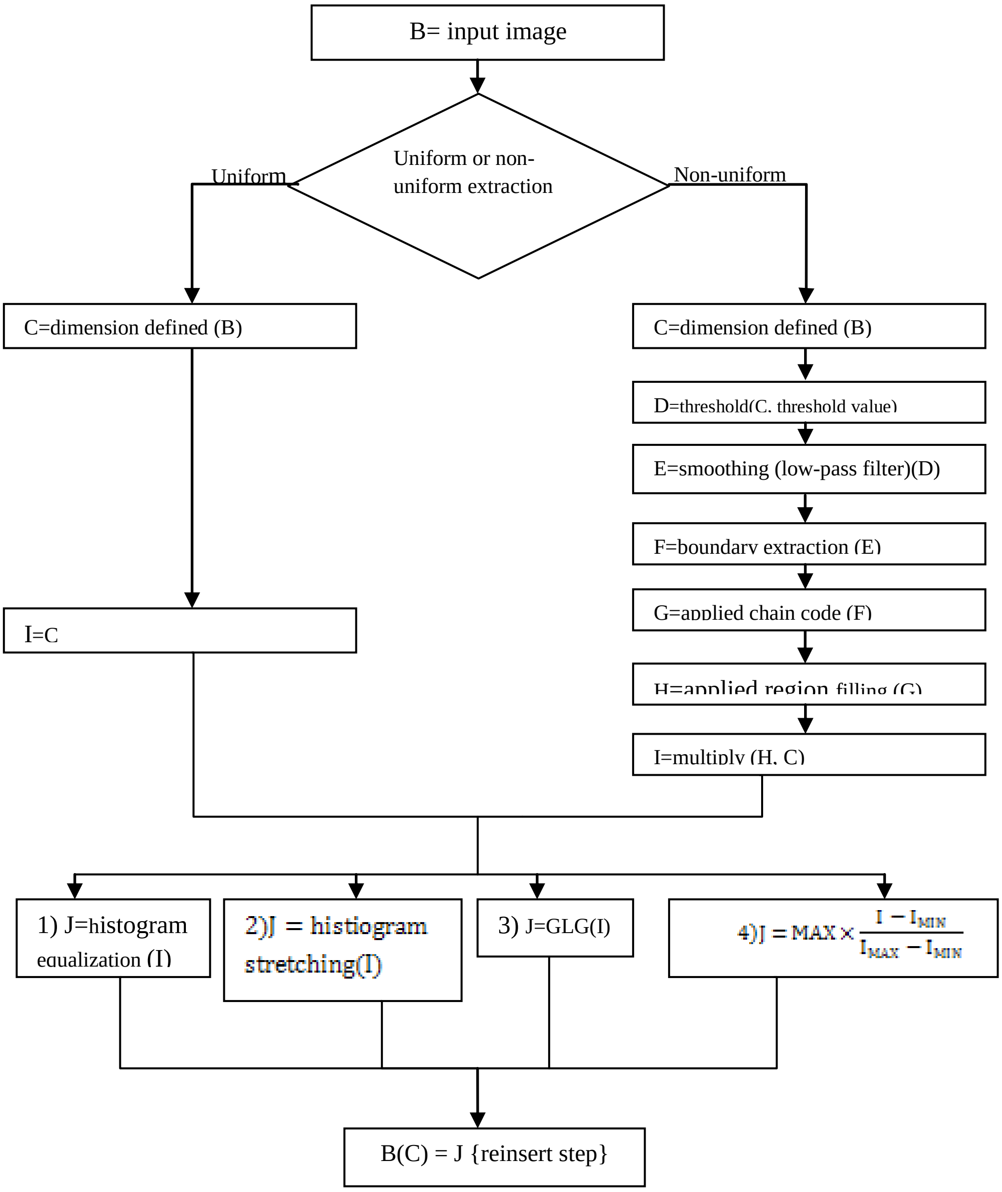
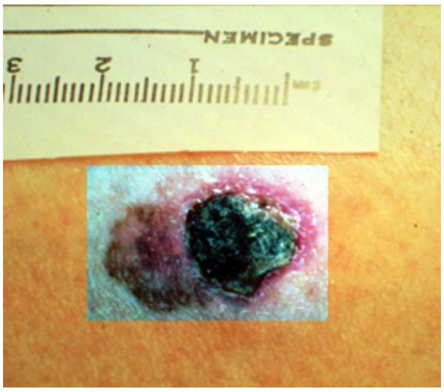
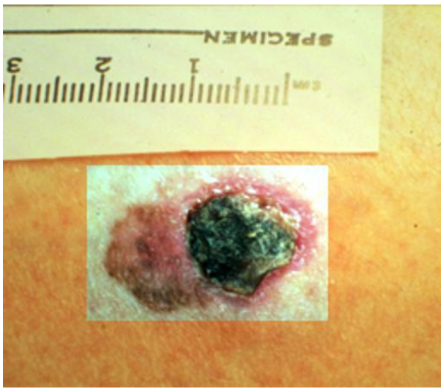


Figure (8); The proposed technique flowchart

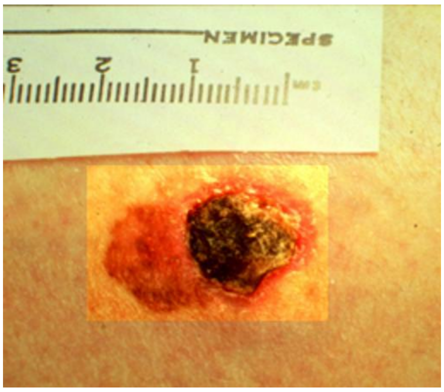
Figure (9) original image



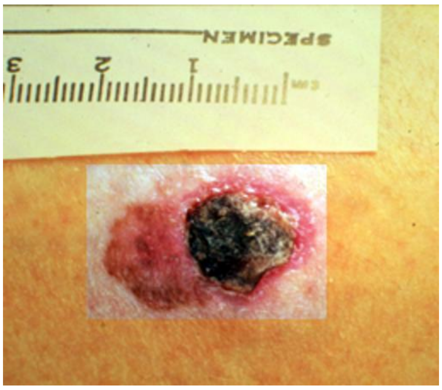
(a) Histogram equilzation result



(b) GLG result



(c) Auto contrast result

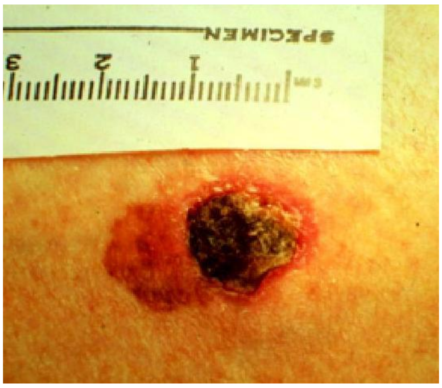


(d) Histogram stretching results

Figure (10); proposed technique results.

(a) histogram equilzation result

(b) GLG result



(c) Auto contrast result

(d) histogram stretching result

Figure (11) contrast enhancement before extraction