Comparison Between Classical Masks and (Odd and Even) Groups Masks for Mycosis Fungoides Disease Skin Image Edges Detection

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Abstract

In the present paper, a comparison between classical masks and (odd and even) masks groups for Mycosis Fungoides disease Skin image edges detection is performed.
The goal is to extract the information known in the image because it is vital to understand the image content as the proposed approach is the comparative edge by masks classical and a new set of Groups masks (odd and even) which consist of 10 masks. The database consists of 40 images reprints different stage of the Mycosis Fungoides disease Skin images 10 images for each stage. The experimental results confirm the effectiveness of the proposed system. and confirm the effectiveness of the proposed(odd and even) Groups masks.

Keywords:

Edge detection ,Skin image detection, Segmentation, Image processing.

1-Introduction

Edge detection is a very important area in the field of Computer Vision. Edges define the boundaries between regions in an image, which helps with segmentation and object recognition. They can show where shadows fall in an image or any other distinct change in the intensity of an image. Edge detection is a fundamental of low-level image processing and good edges are necessary for higher level processing [1] .

Classical methods of edge detection involve convolving the image with an operator (a 2-D filter), which is
constructed to be sensitive to large gradients in the image while returning values of zero in uniform regions. There are an extremely large number of edge detection operators available, each designed to be sensitive to certain types of edges. The geometry of the operator determines a characteristic direction in which it is most sensitive to edges. Operators can be optimized to look for horizontal, vertical, or diagonal edges. Edge detection is difficult in noisy images, since both the noise and the edges contain high frequency content. Attempts to reduce the noise result in blurred and distorted edges. Operators used on noisy images are typically larger in scope, so they can average enough data to discount localized noisy pixels. In[2] results show results in less accurate localization of the detected edges Not all edges involve a step change in intensity. in [3]. The operator needs to be chosen to be responsive to such a gradual change in those cases. So, there are problems of false edge detection, missing true edges, edge localization, high computational time and problems due to noise etc. Therefore, the objective is to do the comparison of various edge detection techniques and analyze the performance of the various techniques in different conditions. The

problem is that in general edge detectors behave very poorly. While their behavior may fall within tolerances in specific situations, in general edge detectors have difficulty adapting to different situations. The quality of edge detection is highly dependent on lighting conditions, the presence of objects of similar intensities, density of edges in the scene, and noise. While each of these problems can be handled by adjusting certain values in the edge detector and changing the threshold value for what is considered an edge, no good method has been determined for automatically setting these values, so they must be manually changed by an operator each time the detector is run with a different set of data[4] this paper is organized as follows; Section 2 deals with the classical masks Mycosis Fungoides disease Skin image edges detection. Section 3 deals with (odd and even) Groups masks for Mycosis Fungoides disease Skin image edges detection, section 4 presents an overview of algorithm with Experimental Results and last section 5 ends the paper with conclusion

2-Classical Edge Detectors

Image data is discrete, so edges in an image often are defined as the local maxima of the gradient. This is the definition we will use here. Edge detection is an important task in image processing. It is a main tool in pattern recognition, image segmentation, and scene analysis. An edge detector is basically a high pass filter that can be applied to extract the edge points in an image. This topic has attracted many researchers and many achievements have been made In these papers [5][6] .

Many classical edge detectors have been developed over time. They are based on the principle of matching local image segments with specific edge patterns. The edge detection is realized by the convolution with a set of directional derivative masks [7] The popular Noise and its influence on edge detection 3 edge detection operators are Roberts, Sobel, Prewitt, Frei-Chen, and Laplacian operators([8],[9],[10] and [7]) They are all defined on a 3 by 3 pattern grid, so they are efficient and easy to apply. In certain situations where the edges are highly directional, some edge detector works especially well because their patterns fit the edges better.

Classical edge detectors use a pre-defined group of edge patterns to match each image segments of a fixed size. 2-D discrete convolutions are used here to find the correlations between the pre-defined edge patterns and the sampled image segment

$$(f * m)(x, y) = \sum \sum f(i, j) m(x - i, y - j) \quad (1)$$

where f is the image and m is the edge pattern defined by

$$m = \begin{array}{|c|c|c|} \hline m(-1,-1) & m(-1,0) & m(-1,1) \\ \hline m(0,-1) & m(0,0) & m(0,1) \\ \hline m(1,-1) & m(1,0) & m(1,1) \\ \hline \end{array},$$

m(i, j) = 0, if (i, j)is not in the defined grid.

These patterns are represented as filters, which are vectors (1-D) or matrices (2-D). For fast performance, usually the dimension of these filters are 1×3 (1-D) or 3×3 (2-D). From the point of view of functions, filters are discrete operators of directional derivatives. Instead of finding the local maxima of the gradient, we set a threshold and consider those points with gradient above the threshold as edge points. Given the source image f(x, y), the edge image E(x, y) is given by

$$E = \sqrt{(f * s)^2 + (f * t)^2}, \quad (2)$$

where s and t are two filters of two orthogonal directions

There are many types of Classical edge detectors such :

2-1 Roberts edge detector

These filters have the shortest support, thus the position of the edges is more accurate.

On the other hand, the short support of the filters make it very vulnerable to noise. The edge pattern of this edge detector makes it especially sensitive to edges with a slope around π/4 . Some computer vision programs use the Roberts edge detector to recognize edges of roads [11]

$\partial f \backslash \partial x = f(i,j) - f(i+1, j+1)$
(3)
$\partial f \backslash \partial y = f(i+1, j) - f(i, j+1)$

This approximation can be implemented by the following masks:

$$M_x = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \qquad M_y = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

(note: Mx and My are is approximations at $(i + 1/2, j + 1/2)$)

2-2 Sobel edge detector

The edge patterns are similar to those of the Prewitt edge detector These filters are similar to the Prewitt edge detector, but the average operator is more like a Gaussian, which makes it better for removing some white noise.[13][16]

The Sobel edge detection mask look for edge in both the horizontal and vertical directions, and then combine this information into a single metric.

$$\begin{bmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix}$$

VERTICAL EDGE (Gy) =s1
HORIZONTAL EDGE (Gx)=s2

EDGE MAGNITUDE $= \sqrt{s_1^2 + s_2^2}$ (4)

EDGE DIRECTION $= \tan^{-1}\left[\frac{s_1}{s_2}\right]$ (5)

2-3 Prewitt edge detector

similar to the Sobel, but with different mask coefficients. The mask are each convolved with the image. At each pixel location we find two numbers: p1, corresponding to the result from the vertical edge mask, and p2, from the horizontal edge mask.
they use these results to determine two metric, the edge magnitude and the edge direction
Consider the arrangement of pixels about the pixel (i, j):

$$\begin{matrix} a_0 & a_1 & a_2 \\ a_7 & [i,j] & a_3 \\ a_6 & a_5 & a_4 \end{matrix}$$

The partial derivatives can be computed by:

$s_x = (a_2 + ca_3 + a_4) - (a_0 + ca_7 + a_6)$
(6)
$t_y = (a_6 + ca_5 + a_4) - (a_0 + ca_1 + a_2)$

The constant c implies the emphasis given to pixels closer to the center of the mask. Setting , they get the Prewitt operator:

$$\begin{bmatrix} -1 & -1 & -1 \\ 0 & 0 & 0 \\ 1 & 1 & 1 \end{bmatrix} \qquad \begin{bmatrix} -1 & 0 & 1 \\ -1 & 0 & 1 \\ -1 & 0 & 1 \end{bmatrix}$$

P1 P2

These filters have longer support. They differentiate in one direction and average in the other direction. So the edge detector is less vulnerable to noise. However, the position of the edges might be altered due to the average operation[13]

Edge magnitude $= \sqrt{p_1^2 + p_2^2}$ (7)

Edge direction $= \tan^{-1}\left[\frac{p_1}{p_2}\right]$ (8)

2-4 Frei-Chen Edge Detector

A 3×3 sub image b of an image f may be thought of as a vector in R9. For example,

$$b = \begin{array}{|c|c|c|} \hline b_4 & b_3 & b_2 \\ \hline b_5 & b_0 & b_1 \\ \hline b_6 & b_7 & b_8 \\ \hline \end{array} \quad \rightarrow \quad b = \begin{bmatrix} b_0 \\ b_1 \\ \vdots \\ b_8 \end{bmatrix}$$

Let V denote the vector space of 3 × 3 sub images. BV , an orthogonal basis for V, is used for the Frei-Chen method. The subspace E of V that is spanned by the sub images v1, v2, v3 and v4 is called the edge subspace of V . The Frei-Chen edge detection method bases its determination of edge points on the size of the angle between the sub image b and its projection on the edge subspace.

$$\underset{v_1}{\begin{bmatrix}1 & \sqrt{2} & 1\\ 0 & 0 & 0\\ -1 & -\sqrt{2} & -1\end{bmatrix}} \quad \underset{v_2}{\begin{bmatrix}1 & 0 & -1\\ \sqrt{2} & 0 & -\sqrt{2}\\ 1 & 0 & -1\end{bmatrix}} \quad \underset{v_3}{\begin{bmatrix}0 & -1 & \sqrt{2}\\ 1 & 0 & -1\\ -\sqrt{2} & 1 & 0\end{bmatrix}} \quad \underset{v_4}{\begin{bmatrix}\sqrt{2} & -1 & 0\\ -1 & 0 & 1\\ 0 & 1 & -\sqrt{2}\end{bmatrix}}$$

$$\underset{v_5}{\begin{bmatrix}0 & 1 & 0\\ -1 & 0 & -1\\ 0 & 1 & 0\end{bmatrix}} \quad \underset{v_6}{\begin{bmatrix}-1 & 0 & 1\\ 0 & 0 & 0\\ 1 & 0 & -1\end{bmatrix}} \quad \underset{v_7}{\begin{bmatrix}1 & -2 & 1\\ -2 & 4 & -2\\ 1 & -2 & 1\end{bmatrix}} \quad \underset{v_8}{\begin{bmatrix}-2 & 1 & -2\\ 1 & 4 & 1\\ -2 & 1 & -2\end{bmatrix}} \quad \underset{v_9}{\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}}$$

$$\theta_E = \cos^{-1}\left(\frac{\sum_{i=1}^{4}(v_i \cdot b)^2}{\sum_{i=1}^{9}(v_i \cdot b)^2}\right)^{\frac{1}{2}} \qquad (9)$$

As you can see from the patterns, the sub images in the edge space are typical edge patterns with different directions; the other sub images resemble lines and blank space. Therefore, the angle θE is small when the sub image contains edge-like elements, and θE is large otherwise[14].

2-5 Canny Edge Detection

Canny edge detection[15] is an important step towards mathematically solving edge detection problems. This edge detection method is optimal for step edges corrupted by white noise. Canny used three criteria to design his edge detector. The first requirement is reliable detection of edges with low probability of missing true edges, and a low probability of detecting false edges. Second, the detected edges should be close to the true location of the edge. Lastly, there should be only one response to a single edge. To quantify these criteria, the following functions are defined:

$$SNR(f) = \frac{A}{n_0} \cdot \frac{\left|\int_{-\infty}^{0} f(x)dx\right|}{\left[\int_{-\infty}^{\infty} f^2(x)\,dx\right]^{\frac{1}{2}}},$$

$$Loc(f) = \frac{A}{n_0} \cdot \frac{|f'(0)|}{\left[\int_{-\infty}^{\infty} f'^2(x)dx\right]^{\frac{1}{2}}},$$

where A is the amplitude of the signal and n0 is the variance of noise. SNR(f) defines the signal-to-noise ratio and Loc(f) defines the localization of the filter f(x). Now, by scaling f to fs, they get the following :

$$SNR(f_s) = \sqrt{s}SNR(f),$$

$$Loc(f_s) = \frac{1}{\sqrt{s}}Loc(f).$$

That is, increasing the filter size increases the signal-to-noise ratio but also decreases the localization by the same factor. This suggests maximizing the product of the two. So the object function is defined as:

$$J(f) = \frac{\left|\int_{-\infty}^{0} f(x)dx\right|}{\left[\int_{-\infty}^{\infty} f^2(x)dx\right]^{\frac{1}{2}}} \cdot \frac{|f'(0)|}{\left[\int_{-\infty}^{\infty} f'^2(x)dx\right]^{\frac{1}{2}}}, \qquad (10)$$

where f(x) is the filter for edge detection. The optimal filter that is derived from these requirements can be approximated with the first derivative of the Gaussian filter,

$$f(x) = -\frac{x}{\sigma^2}e^{-\frac{x^2}{2\sigma^2}}. \qquad (11)$$

The choice of the standard deviation for the Gaussian filter, σ, depends on the size, or scale, of the objects contained in the image. For images with multiple size objects, or unknown size one approach is to use Canny detectors with different σ values. The outputs of the different Canny filters are combined to form the final edge image.

Algorithm

1. Compute f_x and f_y

$$f_x = \frac{\partial}{\partial x}(f * G) = f * \frac{\partial}{\partial x} G = f * G_x$$

$$f_y = \frac{\partial}{\partial y}(f * G) = f * \frac{\partial}{\partial y} G = f * G_y$$

$G(x, y)$ is the Gaussian function

$G_x(x, y)$ is the derivate of $G(x, y)$ with respect to x: $G_x(x, y) = \frac{-x}{\sigma^2} G(x, y)$

$G_y(x, y)$ is the derivate of $G(x, y)$ with respect to y: $G_y(x, y) = \frac{-y}{\sigma^2} G(x, y)$

2. Compute the gradient magnitude

$$magn(i, j) = \sqrt{f_x^2 + f_y^2}$$

3. Apply non-maxima suppression.

4. Apply hysteresis thresholding/edge linking.

2-6 Laplace Operator(LoG)

The three Laplacian masks presented below represent different approximations of the Laplacian, which is the two dimensional version of the second derivative.

Unlike the Sobel and Prewitt edge detection masks, the Laplacian masks are rotationally symmetric, which means edges at all orientations contribute to the result.

$$\nabla^2 f = \frac{\partial^2 f}{\partial x^2} + \frac{\partial^2 f}{\partial y^2}$$

Approximating $\nabla^2 f$:

$$\frac{\partial^2 f}{\partial x^2} = f(i, j+1) - 2f(i, j) + f(i, j-1)$$

$$\frac{\partial^2 f}{\partial y^2} = f(i+1, j) - 2f(i, j) + f(i-1, j)$$

$$\nabla^2 f = -4f(i, j) + f(i, j+1) + f(i, j-1) + f(i+1, j) + f(i-1, j)$$

The Laplacian filter is obtained by taking the average of an 8-connected
neighborhood. The mask is given [16]

$$\begin{bmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{bmatrix} \quad \begin{bmatrix} -1 & -1 & -1 \\ -1 & 8 & -1 \\ -1 & -1 & -1 \end{bmatrix} \quad \begin{bmatrix} -2 & 1 & -2 \\ 1 & 4 & 1 \\ -2 & 1 & -2 \end{bmatrix}$$

All filter type used the process of passing an N*N convolution mask over an image (with N odd and typically greater or equal to 3). The image is processed by aligning each intensity value in the image with the center of the mask in left to right, top to bottom scan of the image. As the scan progress, intensity value passing beneath the center cell of the mask are replaced with the weighted sum of the value stored in the mask and of the intensity value lying beneath the mask.

3- Groups masks (odd and even)

A human skin color model is used to decide either a pixel is skin color or non skin-color[8]. In this research, we use new method called**(odd and even) Groups masks** for Mycosis Fungoides Skin image edge detection .
(odd and even) Groups masks consists :
The shape of masks consists as formal below the most different between Groups is the values

[I-1,J-1]	[I-1,J]	[I-1,j+1]
[I,j-1]	[I,J]	[I,j+1]
[I+1,j-1]	[I+1,J]	[I+1,j+1]

A1	A	A1
A	A1	A
A1	A	A1

The values for Groups masks are shown in figure(1) and figure(2)

	O1	
√3	√5	√3
√5	√3	√5
√3	√5	√3

	O2	
√7	√5	√7
√5	√7	√5
√7	√5	√7

	O3	
√11	√7	√11
√7	√11	√7
√11	√7	√11

	O4	
√13	√17	√13
√17	√13	√17
√13	√17	√13

	O5	
√3	√7	√3
√7	√3	√7
√3	√7	√3

Figure(1): Group masks(Odd)

	E1	
√2	√4	√2
√4	√2	√4
√2	√4	√2

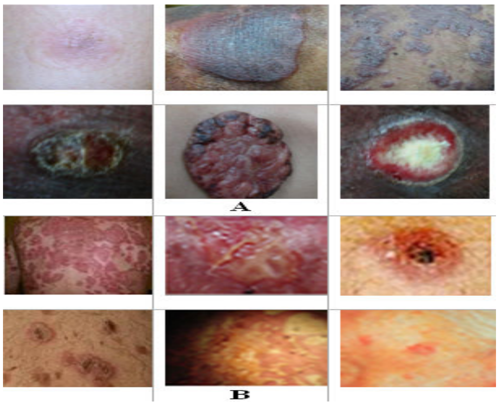
	E2	
√6	√8	√6
√8	√6	√8
√6	√8	√6

	E3	
√10	√6	√10
√6	√10	√6
√10	√6	√10

	E4	
√22	√24	√22
√24	√22	√24
√22	√24	√22

	E5	
√2	√12	√2
√12	√2	√12
√2	√12	√2

Figure(3): Group masks(Even)



two types of images (A)Samples with Mycosis Fungoides diseases Skin images (B) Samples with other diseases shown in figure(2)
Figure(3): The skin library samples, (A) Samples with Skin diseases (B) Samples with other diseases

4.Experimental Results

In this section a detailed experimental comparison of the above stated Classical edge detectors and Group masks (odd and even) has been presented. We have used two types Mycosis Fungoides Skin image databases:
(1) database prepared in our conditions ,images obtained from Al-Sder Hospital.
(2) Skin database [4] and some other images obtained from internet.
Mycosis fungoides is a T-cell lymphoma of the skin. The disease is caused by the proliferation of T-lymphocytes, also known as helper T cells[16].

In this paper divided stages images as Stages in mycosis fungoides(10 images for each stage)

Stage 1
The cancer only affects parts of the skin, which has red, dry, scaly patches, but no tumours. The lymph nodes are not larger than normal.

Stage 2
Either of the following may be true:
• The skin has red, dry, scaly patches, but no tumours. Lymph nodes are larger than normal, but do not contain cancer cells;
• There are tumours on the skin. The lymph nodes are either normal or are larger than normal, but do not contain cancer cells.

Stage 3
• Nearly all of the skin is red, dry, and scaly. The lymph nodes are either normal or are larger than normal, but do not contain cancer cells.

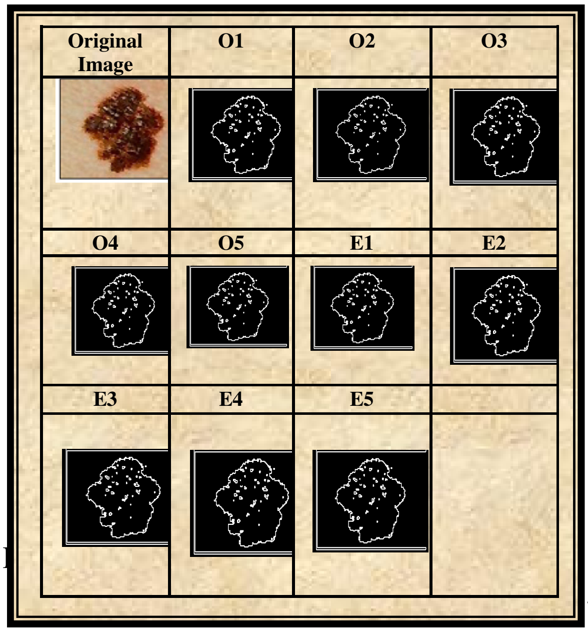
Stage 4
The skin is involved, in addition to either of the following:
• Cancer cells are found in the lymph nodes;
• Cancer has spread to other organs, such as the liver or lung[8].

Experimental Results for Appling Edge Detection mask shown in figure (4-14).
The most common method for evaluating the effectiveness of a segmentation method is subjective evaluation, in which a human visually compares the image segmentation results for separate segmentation algorithms, which is a tedious process and inherently limits the depth of evaluation to a relatively small number of segmentation comparisons over a predetermined set of images. A nother common evaluation alternative is supervised evaluation, in which a segmented image is compared against a manually-segmented or pre-processed reference image.
For Classical edge detectors Canny's edge detection algorithm is computationally more expensive compared to Sobel, Prewitt and Robert's operator. The Canny's edge detection algorithm performs better than all these operators under almost all scenarios. Evaluation of the images showed that under noisy conditions, Canny, Frei-Chen edge

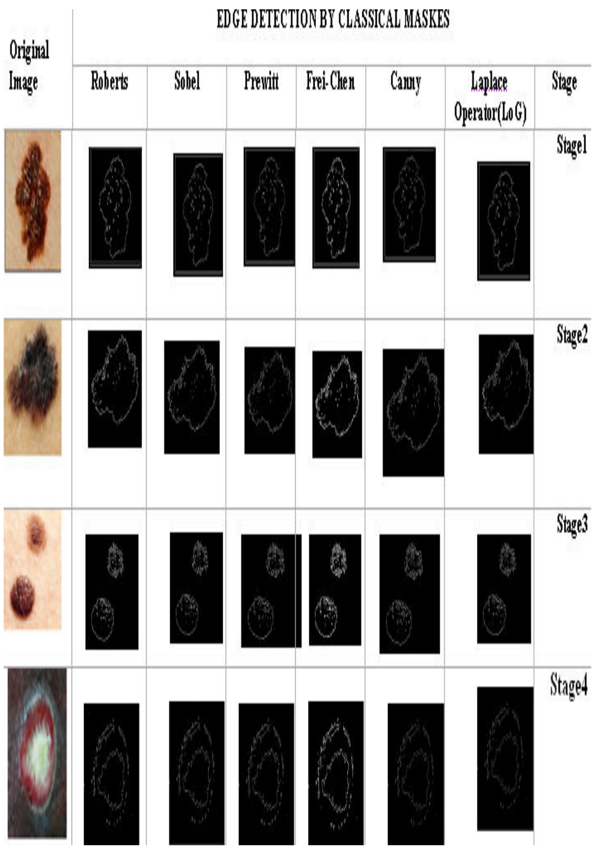
detector ,LoG, Sobel, Prewitt, Roberts's exhibit better performance, respectively.
Finally, the Groups masks (odd and even) is quite useful for for Mycosis Fungoides disease Skin image edges detection and performs better than all these operators under almost all scenarios.

7. Conclusion

new method called Group masks (odd and even) for Mycosis Fungoides Skin image edge detector compare with Classical edge detectors is presented in this paper it uses ten masks determines a characteristic direction in which it is most sensitive to edges . The proposed method is decrease the computation time with generate high quality of edge detection. Experiment results have demonstrated that the proposed scheme for edge detection works satisfactorily for different levels digital images. Another benefit comes from easy implementation of this method. Group masks (odd and even) Group masks for Mycosis Fungoides Skin image Edge detection is necessary to provide a robust solution that is adaptable to the varying noise levels of these images to help distinguish valid image contents from visual artifacts introduced by noise. The experimental results show the satisfying subjective test results and the simulation results are very promising.



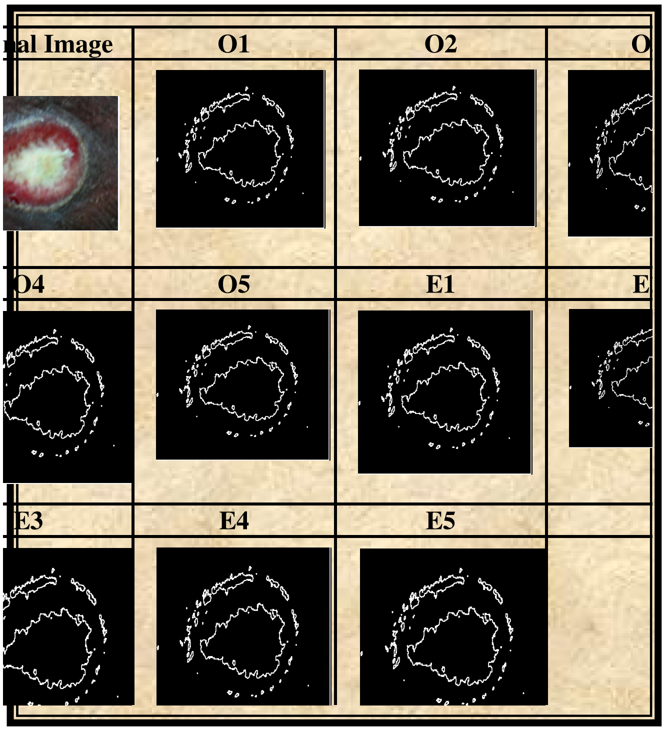
E 1, E 2, E 3, E 4,E5) A for all Mycosis Fungoides Skin image stages



Figure(5):(A):Original Skin Image ,

(B) Edge detection by Classical edge detectors for A for all Mycosis Fungoides Skin image stage

Figure(6)(A):Original Skin Image , (B) Edge detection by (O1, O 2, O 3, O 4, O 5, E 1, E 2, E 3, E 4,E5) A for all Mycosis Fungoides Skin image stages



Figure(7)(A):Original Skin Image
(B) Edge detection by (O1, O 2, O 3, O 4, O 5, E 1, E 2, E 3, E 4,E5) A for all Mycosis Fungoides Skin image stages

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