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A New Edge Detector in CT Scan Images Using Gradient of Weibull Distribution

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Abstract— CT Scan is based on the x-ray principal: as x-rays pass through the body they are absorbed or attenuated (weakened) at differing levels creating a matrix or profile of x-ray beams of different strength. This x-ray profile is registered on film, thus creating an image. In the case of CT. Image processing uses for detecting for objects of CT images. Edge detection; which is a method of determining the discontinuities gray level images, is a very important initial step in Image processing. Many classical edge detectors have been developed over time. Some of the well-known edge detection operators based on the first derivative of the image are Roberts, Prewitt, Sobel which are traditionally implemented by convolving the image with masks. Also Gaussian distribution has been used to build masks for the first and second derivative. However, this distribution has a limit to only symmetric shape. This paper will use to construct the masks. The Weibull distribution which was more general than Gaussian because it has symmetric and asymmetric shape. The constructed masks are applied to images and we obtained good results.

Keywords- Edge detection; Image processing; Weibull Distribution; Gradient; CT scan images.

I. INTRODUCTION

A CT scan is a construction of Computed Tomography scan. It is also known as a CAT (Computer Axial Tomography) scans. CT scanner is a special kind of X-ray machine, which combines many x-ray images instead of just one with the assistance computer. It employs the process of generating a 2-dimensional image with assistance of the computer. In some cases a 3-dimensional image can also be formed by taking many pictures of the same region from varying angles. Density and the Strength of the X-ray beams help in providing a cross-section of the body. CT scan [10] helps in inspecting the interiors of the body, differentiating normal and abnormal structures, and providing the necessary treatment. In recent times, it has become a necessary in locating tumors and giving suitable treatment by radiotherapy. CT scanner can be used now to picture of part of the body, including brain, lungs, kidney, liver and spine [2], [17]. An edge is usually a step change in intensity of the image (CT image). It corresponds to the boundary between two regions or a set of points in the image where luminous intensity changes very sharply [10]. Determination of, whether pixel is an edge point or not, bases on how much its local neighbours respond to a certain edge detector [13].

Over the years, many methods have been proposed for detecting edges in images. Some of the earlier methods, such as the Sobel and Prewitt detectors [11], used local gradient operators [12] to obtain spatial filter masks. The procedure is to compute the sum of products of the mask coefficients with the intensity values in the region encompassed by the mask [3]. Also the Canny edge detector which depends on the Gaussian distribution in obtaining the operators for the gradient and Laplacian masks is a well-known edge detector [9]. In this paper we propose method that will use Weibull Distribution instead of Gaussian distribution to obtain edge detection operators. The advantage of this method is that Gaussian distribution has limitation to only symmetric shape but Weibull Distribution has symmetric and asymmetric shape.

The paper is organized as follows. Section 2 introduces Edge Detection using Gradient. Section 3 explains the Gradient of Weibull distribution. Experimental result is shown in Section 4. Finally this paper presents conclusion and future work in Section 5.

II. EDGE DETECTION USING GRADIENT

In image processing, the gradient is the change in gray level with direction. This can be calculated by taking the difference in value of neighboring pixels

Where ∇f is first order derivative of $f(x,y)$ define as:

$$\nabla f(x,y) = \frac{\partial f(x,y)}{\partial x} + \frac{\partial f(x,y)}{\partial y} \qquad (1)$$

The magnitude of this vector, denoted magn(f), Where

$$\text{magn}(\nabla f) = \sqrt{\left(\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right)} \qquad (2)$$

$$= \sqrt{\left(G_x^{\,2} + G_y^{\,2}\right)}$$

The direction of the gradient vector, denoted dir(f), Where

$$\text{dir}(\nabla f) = \tan^{-1}(G_y / G_x) \qquad (3)$$

The magnitude of gradient provides information about the strength of the edge and the direction of gradient is always perpendicular to the direction of the edge.

This section reviews some of the main edge detection methods, such as the Prewitt method and Gradient of Gaussian edge detector.

The Prewitt method [3] utilizes two masks, M_x and M_y , which are shown in fig. 1, to do convolution on the gray image and then obtain the edge intensities G_x and G_y in the vertical and horizontal directions, respectively. The edge intensity of the mask center is defined as $|G_x|+|G_y|$. If the edge intensity of each pixel is larger than an appropriate threshold T, then the pixel will be regarded as an edge point. Unfortunately, the edge line detected by Prewitt method is usually thicker than the actual edge [16].

-1	0	1
-1	0	1
-1	0	1

Mx

-1	-1	-1
0	0	0
1	1	1

My

Figure 1. Two convolution masks in Prewitt method.

An edge detection operator can reduce noise by smoothing the image, but this adds uncertainly to the location of the edge: or the operator can have greater sensitivity to the presence of edges, but this will increase the sensitivity of the operator to noise. The type of liner operator that provides the best compromise between noise immunity and localization, while retaining the advantages of Gaussian filtering is the first derivative of a Gaussian. This operator corresponds to smooth an image with Gaussian function and then computing the gradient.

The gradient can be numerically approximated by using the standard finite-difference approximation for the first partial derivative in the x and y directions. The operator that is the combination of a Gaussian smoothing filter and a gradient approximation is not rotationally symmetric. The operator is symmetric along the edge and antisymmetric perpendicular to the edge (along the line of the gradient). This means that the operator is sensitive to the edge in the direction of steepest change, but it is insensitive to the edge and acts as a smoothing operator in the direction along the line

I. GRADIENT OF WEIBULL DISTRIBUTION

The Gaussian distribution is the most popularly used as a model in the field of pattern recognition. It is used to build masks for the first and second derivative. However, it has limit to only symmetric shape. We will propose new method that uses Weibull Distribution which is more general than Gaussian because it has symmetric and asymmetric shape.

In this section the characteristic of 1D Weibull distribution will be explained and how calculate 2D Weibull distribution from 1D. The 1D Weibull distributions have the probability density function is given by:

$$\text{1DW}(x;\alpha,\beta) = \begin{cases} \alpha\beta x^{\beta-2} e^{-\alpha x^{\beta}} (\beta - 1 - \alpha\beta x^{\beta}) & x > 0 \\ 0 & \text{elsewhere} \end{cases} \qquad (4)$$

The distribution can be skewed to the right as shown in Fig.3 or can be skewed to the left as shown in Fig.4. [8].

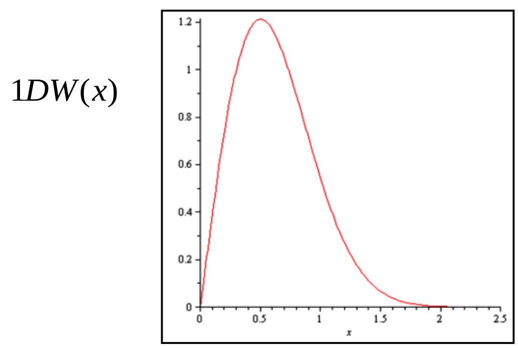

Figure 3. Probability density function of the Weibull distribution (α=1, β=2)

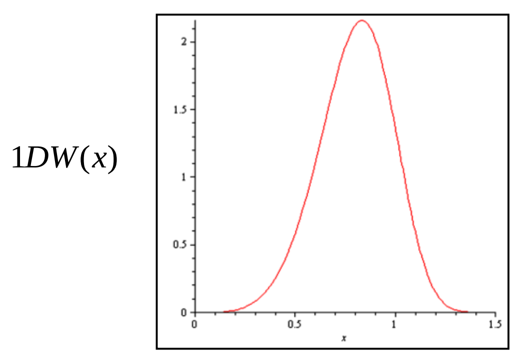

Figure 4. Probability density function of the Weibull distribution (α=1, β=3)

The 2D Weibull distribution can be calculated by multiplying: and $1DW(x;\alpha,\beta)$ by $1DW(y;\alpha,\beta)$ where f is "Eq. (4)" given by:

$$2\mathrm{DW}(x,y;\alpha,\beta) = 1\mathrm{DW}((x;\alpha,\beta)\times 1\mathrm{DW}(y;\alpha,\beta) \quad (5)$$

$$= \begin{cases} \alpha^2\beta^2 x^{\beta-1} y^{\beta-1} e^{-\alpha(x^\beta + y^\beta)} & x>0, y>0 \\ 0 & \end{cases}$$

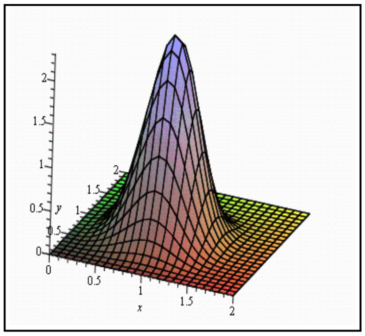

Figure 5. Weibull distribution of two dimensions (α = 1, β = 4)

Fig 5. Show that Weibull distribution of two dimensions when α = 1, β = 4. In the following section we will explain the applying of edge detection using the gradient of the 2D Weibull Distribution.

3.1. Edge Detection using the Gradient of the 2D Weibull Distribution

The gradient mask of $2DW(x,y)$ can be constructed by obtaining the first partial derivative of x, y for $2DW(x,y)$. The first x derivative for $2DW(x,y)$ is given by:

$$= \begin{cases} \alpha^2\beta^2 x^{\beta-2} y^{\beta-1} e^{-\alpha(x^\beta+y^\beta)}(\beta-1-\alpha\beta x^\beta) & x>0, y>0 \quad (6) \\ 0 & \text{Elsewhere} \end{cases}$$

The first y derivative for $2DW(x,y)$ is given by:

$$= \begin{cases} \alpha^2\beta^2 y^{\beta-2} x^{\beta-1} e^{-\alpha(x^\beta+y^\beta)}(\beta-1-\alpha\beta y^\beta) & x>0, y>0 \quad (7) \\ 0 & \text{Elsewhere} \end{cases}$$

Using the first x derivative for $2DW(x,y)$ we can construct M_x mask:

$M_x 2DW$ $(x-dx, y-dy)$	$M_x 2DW$ $(x-dx, y)$	$M_x 2DW$ $(x-dx, y+dy)$
$M_x 2DW$ $(x, y-dy)$	$M_x 2DW(x,y)$	$M_x 2DW$ $(x, y+dy)$
$M_x 2DW$ $(x+dx, y-dy)$	$M_x 2DW$ $(x+dx, y)$	$M_x 2DW$ $(x+dx, y+dy)$

Using the first y derivative for $2DW(x,y)$ we can construct M_y mask:

$M_y 2DW$ $(x-dx, y-dy)$	$M_y 2DW$ $(x-dx, y)$	$M_y 2DW$ $(x-dx, y+dy)$
$M_y 2DW$ $(x, y-dy)$	$M_y 2DW(x,y)$	$M_y 2DW$ $(x, y+dy)$
$M_y 2DW$ $(x+dx, y-dy)$	$M_y 2DW$ $(x+dx, y)$	$M_y 2DW$ $(x+dx, y+dy)$

It is needed to calculate two increments (d) one for x (dx) and the other for y (dy).

After constructing the masks, they should be normalized. The positive values are added then divided by their sum to obtain 1 and the negative values are computed in the same way to obtain –1, because the sum of the gradient mask should be equal zero.

The obtained masks at α = 1, β =2 are as follows:

0.6951	**1.5025**	**0.9850**
0	**0**	**0**
-0.3538	**-0.7648**	**-0.5014**

M_x

0.6951	**0**	**-0.3538**
1.5025	**0**	**-0.7648**
0.9850	**0**	**-0.5014**

M_y

After normalization we got these results:

0.2184	**0.4721**	**0.3095**
0	**0**	**0**
-0.2184	**-0.4721**	**-0.3095**

M_x

0.2184	**0**	**- 0.2184**
0.4721	**0**	**- 0.4721**
0.3095	**0**	**-0.3095**

M_y

The obtained masks at α = 1, β =3 are as follows:

0.1550	**1.2799**	**0.9149**
0.1785	**1.4738**	**1.0535**
-0.2606	**-2.1526**	**-1.5388**

0.1550	**0.1785**	**-0.2606**
1.2799	**1.4738**	**-2.1526**
0.9149	**1.0535**	**-1.5388**

After normalization we got these results:

0.0307	**0.2532**	**0.1810**
0.0353	**0.2915**	**0.2084**
-0.0660	**-0.5447**	**-0.3894**

0.0307	**0.0353**	**-0.0660**
0.2532	**0.2915**	**-0.5447**
0.1810	**0.2084**	**-0.3894**

II.EXPERIMENTAL RESULTS

We present in this section our experimental results of using Weibull Distribution in detecting edges using Gradient of this distribution.

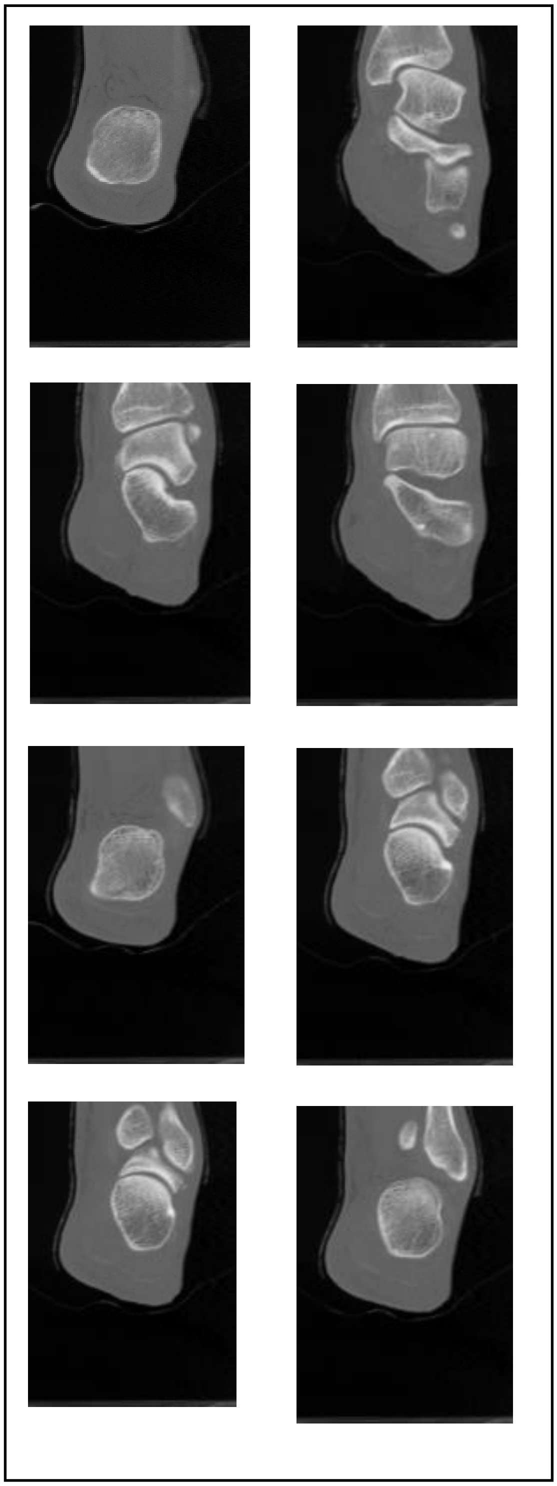

Figure 6. Original Images used in edge detection

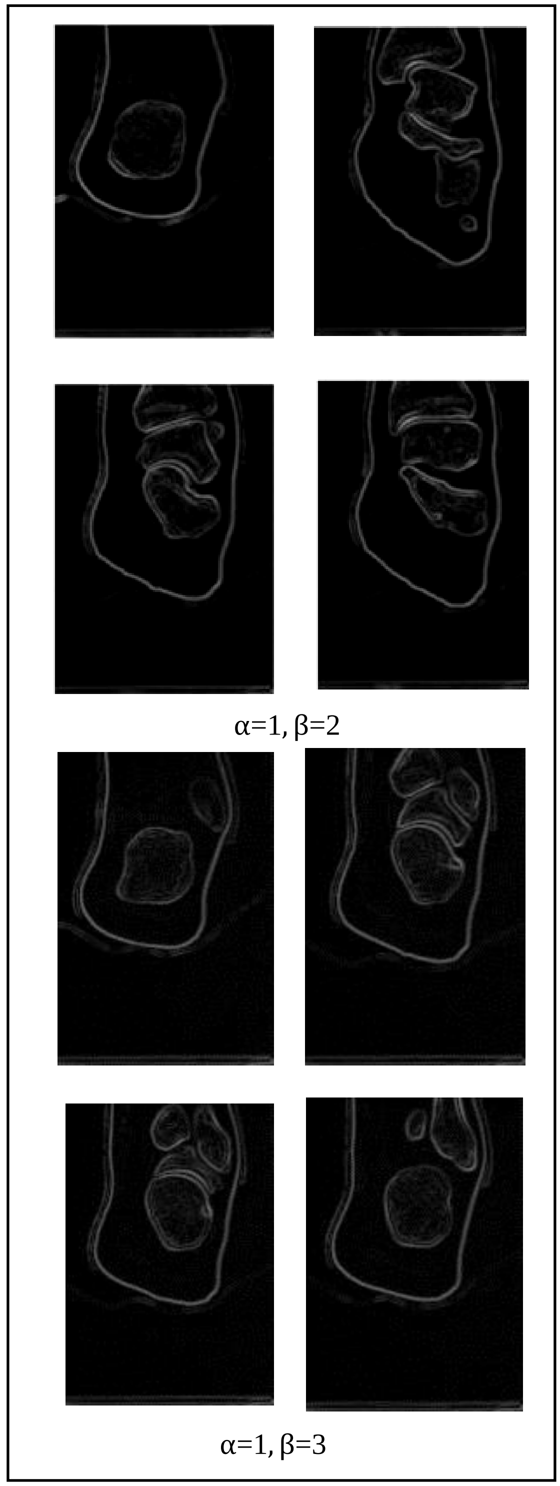

Figure 7. Results of the new Gradient detector of Weibull of size 3x3

In Fig 6. We select eight original CT scan images for bone from different sides and in Fig7. The Images applied with the proposed method to achieve edge detection with Weibull distribution. We notice it is better than the gradient of Gaussian method it produces thinner edges and less sensitive to noise. This is because the Gaussian distribution has limit to only symmetric shape but Weibull distribution has symmetric and asymmetric shape.

III. CONCLUSION AND FUTURE WORKS

Using first derivative in edge detection was depend on Gaussian works well when the image contains sharp intensity transitions and low noise, while Edge detection using LOG make better localization, especially when the edges are not very sharp. We proposed new method that uses Weibull Distribution instead of Gaussian distribution to build masks for the first and second derivative and for smoothing image.

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Ali El-Zaart was a senior software developer at Department of Research and Development, Semiconductor Insight, Ottawa, Canada during 2000-2001. From 2001 to 2004, he was an assistant professor at the Department of Biomedical Technology, College of Applied Medical Sciences, King Saud University. From 2004-2010 he was an assistant professor at the Department of Computer Science, College of computer and information Sciences, King Saud University. In 2010, he promoted to associate professor at the same department. Currently, his is an associate professor at the department of Mathematics and Computer Science, Faculty of Sciences; Beirut Arab University. He has published numerous articles and proceedings in the areas of image processing, remote sensing, and computer vision. He received a B.Sc. in computer science from the Lebanese University; Beirut, Lebanon in 1990, M.Sc. degree in computer science from the University of Sherbrooke, Sherbrooke, Canada in 1996, and Ph.D. degree in computer science from the University of Sherbrooke, Sherbrooke, Canada in 2001. His research interests include image processing, pattern recognition, remote sensing, and computer vision.