Analysis of various Edge detection methods for X-ray images

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Abstract*—X-Ray images are undoubtedly one of the earliest yet most informative ways of analyzing anomaly in bones. X-Ray is one of the oldest and most frequently used devices to capture human bones. An X-ray can capture images of any bone in the body [2]. Image processing has attained the widespread domain, the engineering world witnesses its advancements; and also it reached to the public [4]. The use of Magnetic Resonance Imaging (MRI), computed tomography (CT), digital mammography and other imaging modalities is ever flourishing as critical peripherals in diagnostic techniques [5]. Image segmentation is an important headway in the field of image analysis and is used in a variety of applications including pattern recognition, object detection, and medical imaging [1], which is considered to be as one of the fundamental demands in the field of image processing and computer vision. The task of image segmentation can be stated as the partition of an image into different meaningful regions with homogeneous characteristics using discontinuities or similarities of the image such as intensity, color, tone or texture, and so on [2]. Plentiful numbers of techniques have been developed for image segmentation [3–5].

Keywords—Edge detection; detecting edge; edge detection methods.

I. INTRODUCTION

Image-processing techniques have been researched over years for better analyzing the output of medical imaging systems to get the advantage of analyzing the symptoms of the patients with more ease. Edge detection plays a pivotal role in many medical imaging modalities through automatic means or enabling the manual delineation of anatomical structures [25]. Stepped edges, lines and junction usually convey the most relevant information of an image; hence it is important to detect them in a reliable way [4], [5]. Edge detection has been extensively analyzed in computer vision. Edge is defined as an image point where gradient of image intensity function reaches to its local maximum value. Edges are the curves where rapid changes occur in brightness or in the spatial derivatives of brightness [6]. The changes in the brightness are the place in the image is because of:

1) Surface orientation changes discontinuously
2) One object occludes another
3) A cast shadow line appears
4) There is a discontinuity in surface reflectance properties.

For segmenting the image, computer vision locates a discontinuity in image brightness or its derivatives. Edge detection is the technique that yields pixels lying only on the boundary between regions. In practice, this set of pixels seldom characterizes a boundary completely because of noise, breaks in the boundary from non-uniform illumination and other effects that introduce spurious intensity discontinuities.

X-rays are a form of radiant energy, like light or radio waves. In contrast to light, x-rays can penetrate the body, which allows a radiologist to produce pictures of internal structures. Segmentation subdivides an image into its constituent regions or objects. Image segmentation algorithms are primarily based on one of the two basic properties of intensity values, i.e. discontinuity and similarity. In the former class, the approach is to partition an image based on sudden changes in intensity such as edges in an image [1-4]. Edge detection is by far the most common approach for detecting meaningful discontinuities in intensity values; such discontinuities are detected by using first & second order derivatives. The first order derivative of choice in image processing is the gradient. The second order derivatives of choice in image processing are generally computed using Laplacian. Sobel, Prewitt and Roberts find edges by thresholding the gradient for the log. For Sobel and Prewitt methods, we can choose to detect horizontal edges, vertical edges or both. Laplacian of a Gaussian (LOG) finds edges by calculating the zero crossing after filtering with a Gaussian filter. Zero crossing finds edges by calculating the Zero crossing after filtering with a user-specified filter. Canny finds the edge by looking for local maxima of the gradient. The gradient is calculated by finding the derivative of a Gaussian filter. The method considers two thresholds to detect strong and weak edges, and includes the weak edges in the output only if they are connected to strong edges. Therefore; this method is more likely to detect true weak edges. Sobel edge detection operator is computationally difficult than Prewitt edge detection operator. Prewitt edge detection method is fairly simpler to implement computationally than the Sobel operator. But it tends to produce somewhat noisy results. Robert edge detection operator is one of the earliest and simplest edge detectors in digital image processing. Log performs smoothening of the image (thus reducing noise) and it computes the Laplacian, which yields a double edge image. Zero crossing edge detector

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is based on the same concept as the LOG method but the convolution, is carried out using a specified filter. Canny edge detector is the most powerful edge detection operator provided by function edge. MRI, Cancer and X-Ray images often consist of the important and meaningful edges (i.e. bones). The basic objective of this paper is to detect the edges in the medical images. In case of medical image segmentation, the aim of segmentation is to [3]:

1) Study anatomical structures.
2) Identify Region of Interest i.e. locate tumor, lesion and other abnormalities.
3) Measure tissue volume to measure growth of tumor (also decrease in size of tumor with treatment).
4) Help in treatment planning prior to radiation therapy, in radiation dose calculation.
5) Helps to distinguish one anatomic structure from other.

Some of the mainly used edge detection techniques are discussed herewith:

Sobel operator: The Sobel edge detection based on Sobel operator has advantages of emphasizing the central part of the edge. It relies on central differences but gives greater weight to the central pixels when averaging [13], [14]. The partial derivatives of the Sobel operator are calculated as

$$G_x=(a_2+2a_3+a_4)-(a_0+2a_7+a_6)$$

and $$G_y=(a_6+2a_5+a_4)-(a_0+2a_1+a_2).$$

The sobel masks in the 3*3 matrix form are given as

$$G_x=\begin{vmatrix}-1 & -2 & -1\\ 0 & 0 & 0\\ 1 & 2 & 1\end{vmatrix} \quad \text{and} \quad G_y=\begin{vmatrix}-1 & 0 & 1\\ -2 & 0 & 2\\ -1 & 0 & 1\end{vmatrix}.$$

Canny operator: Canny edge detector defines edges as zero-crossings of second derivatives in the direction of the greatest first derivative. The Canny edge detector operator works in a multi-stage process [16]. Gaussian convolution is used to smooth the image first and then, to highlight the regions of the image with high spatial derivatives, a 2D first derivative operator is applied to the smoothed image. The algorithm then tracks along the top of the ridges and sets all the pixels to zero that are not actually on the top of the ridge so as to give a thin line in the output. This process is known as non-maximal suppression.

Prewitt operator: The Prewitt edge detector based on Prewitt operator approximates the first derivatives. This operator does not place any pixels those are closer to the center of the mask. The direction of gradient mask is given by the mask giving maximal response. The arrangement of pixels about the central pixel [*i*, *j*] as shown below:

$$\begin{vmatrix}a0 & a1 & a2\\ a7 & [i,j] & a3\\ a6 & a5 & a4\end{vmatrix}$$

The Prewitt operator mask is obtained as

$$G_x=\begin{vmatrix}-1 & -1 & -1\\ 0 & 0 & 0\\ 1 & 1 & 1\end{vmatrix} \qquad \text{and } G_y=\begin{vmatrix}-1 & 0 & 1\\ -1 & 0 & 1\\ -1 & 0 & 1\end{vmatrix}$$

The Prewitt mask differentiates in one direction and averages in other direction, so edge detection is less vulnerable to noise.

Zero-cross operator: The zero crossing detector looks for places in the Laplacian of an image where the value of the Laplacian passes through zero --- *i.e.* points where the Laplacian changes sign. Such points often occur at `edges' in images --- *i.e.* points where the intensity of the image changes rapidly, but they also occur at places that are not as easy to associate with edges. It is best to think of the zero crossing detector as some sort of feature detector rather than as a specific edge detector. Zero crossings always lie on closed contours, and so the output from the zero crossing detector is usually a binary image with single pixel thickness lines showing the positions of the zero crossing points.The starting point for the zero crossing detector is an image which has been filtered using the Laplacian of Gaussian filter.

(Laplacian of Gaussian) LoG operator: Laplacian operator is a second order derivative operator. It subtracts the brightness values of each of the neighboring pixels from the central pixel. When a discontinuity is present within the neighborhood in the form of a point, line or edges, the result of the Laplacian is a non-zero value. It may be either positive or negative depending whether the central point lies with respect to the edges. It is rotationally invariant. The Laplacian operator does not depend on direction as long as they are orthogonal [15].

The 3×3 Laplacian operator is given by

$$\begin{vmatrix}-1 & -1 & -1\\ -1 & 8 & -1\\ -1 & -1 & -1\end{vmatrix}$$

Robert's operator: The main objective is to determine the difference between adjacent pixels, one way to find an edge is to explicitly use {+1,-1} that calculates the difference between adjacent pixels. In practice, the Robert kernel is too small to reliably find edges in the presence of noise [13], [14]. The Roberts operator masks are given by

$$G_x=\begin{vmatrix}-1 & 0\\ 0 & 1\end{vmatrix} \qquad G_y=\begin{vmatrix}0 & -1\\ 1 & 0\end{vmatrix}$$

The two individual images Gx and Gy will be combined to get result. The Robert cross kernels are relatively small. Therefore they are highly susceptible to noise.

The organization of the paper is as follows. Section-II gives an overview of the previous work carried out in this field. Section-III deals with the methodology to detect edges in the medical images, Section-IV gives experimental analysis & discussion lastly Section-V gives the conclusion and follows the references.

II. LITERATURE SURVEY

Edge detection of the bones from medical images plays an important role not only in fracture detection [5] but also helps in surgery, quantitative analysis and in surgery planning. Segmentation is an important arena of research in different modalities like CT, MRI and X-ray. In case of X-ray images, the segmentation of bones is quite challenging. This is because of the reason that the bone boundaries are less distinct in X-ray images as compared to images in CT or MRI [6]. Manos et al. [7] applied region based algorithms involving region growing, region merging and region labelling to segment hand and wrist bones. A fuzzy set algorithm has been used by El Feghi et al. [8] to segment bone in lateral skull x-ray images. The algorithm proposed by them, however suffers from the disadvantage of disjoined segmented regions. Vinhais et al. [9] used a deformable prior model to segment the rib cage in posterior-anterior chest X-ray images which is deformed using a deformation grid. The segmented output thus produced defines the lung region, which is further used in Computer aided diagnosis system. Zhanjun Yue et al. [10] , devised a rib finding algorithm that uses Hough transform to approximate and finally localize the rib bones using active contour model in chest radiographs. Yuchong Jiang et al. [11] used Geodesic active contour incorporating prior shape information to segment the leg bone. The proposed algorithm is robust to background noise of the casting material overlaying on the fractured leg. Ying Chen et al. [12] worked on developing a code based on model to automatically extract femur bone from X-ray images. Initially a model femur contour is registered to the X-ray image, followed by active contour with shape constrains, that refines the contour. G. Behielset al. [13] uses active shape model (ASM), involving a regularizing smoothness constrain to segment femur, humor and calcaneus bones in the human body.

III. METHODOLOGY

For segmenting edges of the X-ray images, we proceeded through the following steps.

Step 1. First take an X-ray image.
Step 2. Apply edge detection technique.
Step 3. Calculate MEAN, Standard Deviation (S.D.).
Step 4. Results are to be tabulated.
Step 5. End.

The X-Ray images have been taken as input images. We have applied different edge detection techniques; Sobel, Prewitt, Canny, Log, Zero-cross & Roberts. We have checked these methods and the resultant values of mean & standard deviation are represented in tables. Same is represented by graph also.

IV. EXPERIMENTAL ANALYSIS AND DISCUSSION

In this experimental work, we have considered four distinct X-Ray images. We have applied the above mentioned algorithm on these images. MATLAB has been used to carry out this experimental work. Figure-1 shows original medical images of X-Ray, which are taken for experimental analysis. Figure-2 shows the images, which are obtained by applying Sobel edge detection method on all the four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in table-1. Figure-3 shows the images, which are obtained by applying Canny edge detection method on all four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in table-1. Figure-4 shows the images, which are obtained by applying Prewitt edge detection method on all four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in table-1. Figure-5 shows the images, which are obtained by applying zero-cross edge detection method on all the four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in table-1. Figure-6 shows the images, which are obtained by applying LOG edge detection method on all four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in table-1. Figure-7 shows the images, which are obtained by applying Roberts's edge detection method on all four types of X-Ray images. The mean & standard deviation is evaluated for resultant image as shown in Table-1. And same is also predicted through Graph-1.

Image 1 Image 2

Image 3 Image 4

Fig 1: Original X-ray images

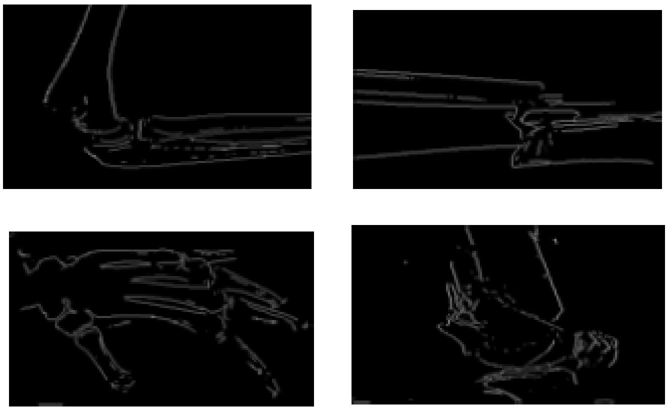


Fig 2: Edge detection using Sobel operator

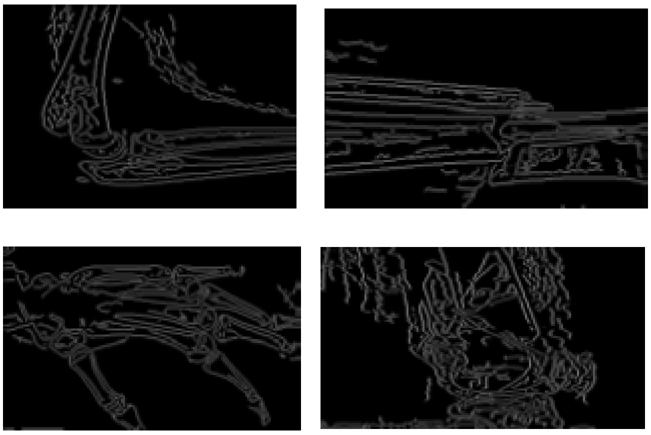


Fig 3: Edge detection using Canny operator

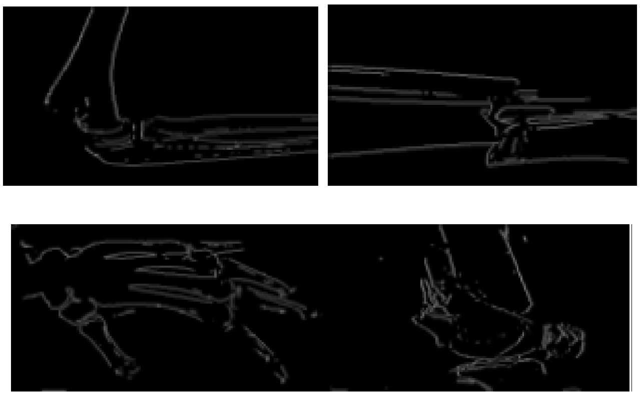
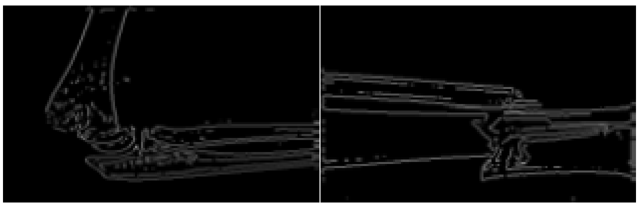


Fig 4: Edge detection using Prewitt operator



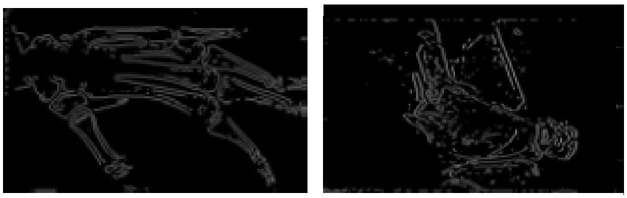


Fig 5: Edge detection using Zero-cross operator

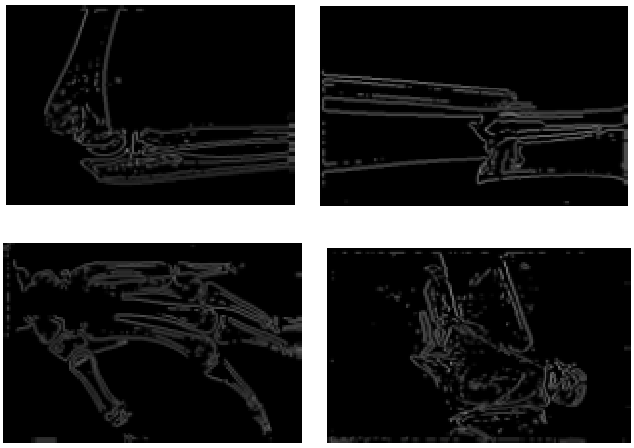


Fig 6: Edge detection using Log operator

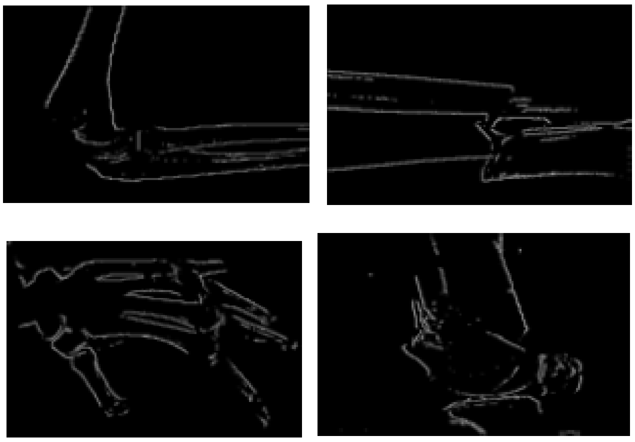
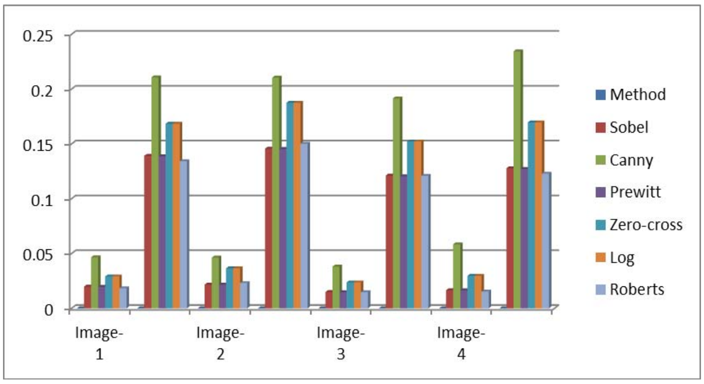


Fig 7: Edge detection using Roberts operator

	Image-1		Image-2		Image-3		Image-4	
Method	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Sobel	0.0198	0.1392	0.0217	0.1457	0.0149	0.1211	0.0166	0.1278
Canny	0.0466	0.2107	0.0464	0.2104	0.0381	0.1914	0.0584	0.2345
Prewitt	0.0196	0.1387	0.0216	0.1455	0.0147	0.1205	0.0165	0.1272
Zero-cross	0.0292	0.1684	0.0365	0.1875	0.0237	0.1522	0.0297	0.1696
Log	0.0292	0.1684	0.0365	0.1875	0.0237	0.1522	0.0297	0.1696
Roberts	0.0183	0.1342	0.0231	0.1501	0.0148	0.1209	0.0153	0.1229

Table1- Shows the Mean and Standard deviation for various edge detection methods on X-ray images.



Graph 1- Graph showing various edge detection methods vs. Standard deviation and Mean.

V. CONCLUSION

In this work, four distinct X-ray images have been considered for detecting edges using various types of edge detection methods. Sobel, Canny, Prewitt, Roberts, Zero cross and Log operators have been used to detect the edges. The results are analyzed, compared and also evaluated through the quality metrics, mean and standard deviation. This work concludes that the choice of edge detection method on the X-ray images depends upon the type of image. For the X-Ray images, canny edge detection method is the best method. From this experimental work it is also observed that Zero Cross and LOG edge detection methods also give good results for all the X-ray images.

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