Edge Detection of Femur bone – A Comparative Study

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***Abstract*-Edge detection of femur in X – ray images is an important pre processing step in segmentation and 3 – D reconstruction of femur. A typical femur image is generally very noisy. A lot of edges caused by the muscles and other bones can easily mislead the edge detection algorithm. Particularly, the femoral head overlapping the pelvic bone makes it very difficult to get a clear edge of the femur head. The edge caused by the abdominal muscles around the femur shaft can also mislead the edge detection algorithm. These extraneous edges and noise make edge detection very difficult and challenging, which is not well solved. Classical edge detectors fail miserably due to the high inhomogeneous nature of the femur X – ray images. This paper compares a new approach to edge detection of femur X – ray images using Wavelet transforms with classical edge detectors. The Wavelet based edge detection algorithm combines the coefficients of wavelet transforms on a series of scales and significantly improves the result. It is found that Wavelet based technique works much better than classical edge detectors.**

Key words: Femur, Edge detection, Wavelet Transforms

1.0 INTRODUCTION

Edge detection (ED) is an important task in image processing and has been the principal tool in image segmentation, scene analysis and pattern recognition. ED is usually performed on various types of medical images such as computed tomography, magnetic resonance and X – ray images. ED in computed tomography and magnetic resonance are much easier than that in X – ray images, because the bones have clearer boundaries segregation in computed tomography and magnetic resonance. In contrast, ED of bones in X- ray images is very difficult, challenging and not well addressed. Edges in images can be mathematically defined as local singularities. Until recently, Fourier transform has been used as the main mathematical tool for analyzing singularities. However, the Fourier transform possesses some noticeable shortcomings as it global and not well adapted to local singularities, thus it is hard to find location and spatial distribution of singularities. Wavelet analysis is a local analysis and it is especially suitable for time – frequency analysis [1], which is an essential feature for singularity detection. With enrichment and the subsequent growth in wavelet literature and its application, the wavelet transforms have been found to be remarkable mathematical tool to analyze the singularities including the edges and further to enhance the detecting capabilities.

The pioneer work of Mallat and Zhong first or second derivative based wavelet functions can be used for multi-scale edge detection. Most multi-scale edge detectors smooth the input signal at various scales i.e.., edges from their first or second derivatives. Edge locations are related to the extrema of the first derivative of the signal and the zero crossings of the second derivative of the signal [3] and [4]. It was also pointed out that first derivative wavelet functions are more appropriate for edge detection, since the magnitude of wavelet modulus represents the relative strength of the edges and therefore enable to differentiate meaningful edges from small fluctuations normally caused by noise. To further improve the robustness of multi scale edge detector, Mallat and Zhong [3] also investigated the relations between singularity (Lipschitz regularity) and the proportion of multi scale edges across wavelet scales.

In a femur X – ray image, the femoral head region contains non – uniform texture pattern due to the trabeculae and the femoral shaft region has non – uniform intensity due to the hollow interior within solid bony walls. Moreover femoral head overlaps with pelvic bone [8]. Owing to this complex architecture of femur bone, the classical edge detection algorithms including the optimal Canny's edge detector fail miserably. In this paper, an attempt has been made to explore the best possible edge detector especially for femur bone extracted from hips X – ray image. The failure of classical edge detectors in this application area motivated authors to consider the wavelet based technique for femoral edge detection. Finally, the relative performance is examined on using the classical and wavelet based ED algorithms on femur X – ray image.

2.0 CLASSICAL EDGE DETECTORS

ED is a terminology in image processing, which refer to algorithms that aim at identifying points in a digital image at which the image brightness changes sharply or more formally has discontinuities. There are many methods of edge detection that have been published mainly differ in

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the types of smoothing filters that are applied and the way the measures of edge strength are computed. As many edge detection methods rely on the computation of image gradients, they also differ in the types of filters used for computing gradient estimates in the X– and Y – directions.

2.1 Robert's Cross Operator

The Robert's cross operator performs a simple, quick to compute, 2 – D spatial gradient measurement on an image. It thus highlights regions of high spatial frequency which often corresponds to edges. Pixel values at each point in the output represent the estimated absolute magnitude of the spatial gradient of the input image at that point. In theory the operator consists of a pair of 2×2 convolution kernels as shown below. One kernel is simply the other rotated by 90°.

$$G_x = \begin{bmatrix} +1 & 0 \\ 0 & -1 \end{bmatrix} \quad G_y = \begin{bmatrix} 0 & +1 \\ -1 & 0 \end{bmatrix} \tag{1}$$

These kernels are designed to respond maximally to edges running at 45° to the pixel grid, one kernel for each of the two perpendicular orientations.

The edge gradient magnitude is given by,

$$|G| = \sqrt{G_X^2 + G_Y^2} \cong |G_X| + |G_Y| \tag{2}$$

The angle of orientation of the edge giving rise to the spatial gradient is given by,

$$\theta = \arctan\left(\frac{G_X}{G_Y}\right) - \frac{3\pi}{4} \tag{3}$$

2.2 Sobel Operator

The Sobel operator performs a 2 – D spatial gradient measurement on an image and typically it is used to find the approximate absolute gradient magnitude at each point in an input image. In theory the operator consists of a pair of 3×3 convolution kernel as shown below.

$$G_X = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad G_Y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \tag{4}$$

These kernels are designed to respond maximally to edges running vertically and horizontally relative to the pixel grid, one kernel for each of the two perpendicular orientations.

The edge gradient magnitude is given by,

$$|G| = \sqrt{G_X^2 + G_Y^2} \cong |G_X| + |G_Y| \tag{5}$$

The angle of orientation of the edge giving rise to the spatial gradient is given by,

$$\theta = \arctan\left(\frac{G_X}{G_Y}\right) \tag{6}$$

2.3Prewitt Compass Edge Detector

Compass edge detection is an alternative approach to the differential gradient edge detection. When using compass edge detection the image is convolved with a set of (in general 8) convolution kernels each of which is sensitive to edges in a different orientation. For each pixel the local edge gradient magnitude is estimated with the maximum response of all 8 kernels at this pixel location.

$$|G| = Max(|G_i| : i = 1 \quad to \quad n \tag{7}$$

Where G_i is the response of the kernel 'i' at the particular pixel location and 'n' is the number of convolution kernels. The local edge orientation is estimated with the orientation of the kernel that yields the maximum response. Two templates out of the set of 8 for the Prewitt kernel is given below.

$$\begin{bmatrix} -1 & 1 & 1 \\ -1 & -2 & 1 \\ -1 & 1 & 1 \end{bmatrix} \qquad \begin{bmatrix} 1 & 1 & 1 \\ -1 & -2 & 1 \\ -1 & -1 & 1 \end{bmatrix} \tag{8}$$

$\theta = 0°$ $\qquad$ $\theta = 45°$

The whole set of 8 kernels is produced by taking one of the kernels and rotating its coefficients circularly. Each of the resulting kernels is sensitive to an edge orientation ranging from $0°$ to $315°$ insteps of $45°$, where $0°$ corresponds to a vertical edge.

2.4 Zero Crossing Detector

The zero crossing detector looks for places in the Laplacian of an image where the value of the Laplacian passes through zero, ie…points where the Laplacian changes sign. Such points often occur at edges in images, i.e… the points where the intensity of the 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 edge detector.

The core of the zero crossing detector is the Laplacian of Gaussian filter. Once the image has been Laplacian of Gaussian filtered, it only remains to detect the zero crossings. This can be done in several ways. The simplest is to threshold the Laplacian of Gaussian output to zero and a more accurate approach is to perform some kind of interpolation to estimate the position of the zero crossing to sub – pixel precision.

2.5 Canny Edge Detector

The Canny operator was designed to be an optimal edge detector. The Canny operator works in a multistage process. First of all the image is smoothed by Gaussian convolution, then a simple 2 – D first derivative operator is applied to the smoothed image with high first spatial derivatives. The effect of the Canny operator is determined by three parameters. i.e… the width of the Gaussian kernel used in the smoothing phase, the lower and upper thresholds used by the tracker. The upper tracking threshold can be set quite high and the lower threshold quite low for good results.

3.0 PROPOSED WAVELET BASED EDGE DETECTOR

Wavelet transform has an ability to characterize the local regularity of functions. The edges of an image $f(x,y)$, correspond to singularities, thus related to the local maxima of the wavelet transform modulus. Therefore, the wavelet transform is an effective tool for edge detection. The wavelet transform can be interpreted as a multi scale edge detector representing the singularity content of the image at multiple scales. Wavelet domain statistical image model have several distinct advances over pixel domain models. Because the wavelet coefficients are approximately decorrelated, a simple dependency structure between the coefficients is sufficient to capture most of the joint statistics of the pixel values. In addition, the natural multi resolution structure of wavelet transform algorithm enable us to process the under laying image at a number of different scales with minimal response.

3.1 Mallat's wavelet

Stephane Mallat's pioneer work is a link between wavelets and edge detection [3]. Mallat's method not only finds edges, but classifies them into different types as well. In this paper we implement the method of mallat to mutiscale edge detection of femur bone. Mallat defines a wavelet as a function of zero average, $\int_{-\infty}^{\infty}\psi(t)dt = 0$

Which is dilated with scale parameter 's' and translated by 'u' [6].

$$\psi_{u,s} = \frac{1}{\sqrt{s}}\psi\left[\frac{t-u}{s}\right] \quad (9)$$

Unlike the sine and cosine functions, wavelets toward quickly zero as their limits approach to $\pm\infty$. Mallat notes that the derivative of a smoothing function is a wavelet with good properties [3]. Such a wavelet is shown in Fig. 1

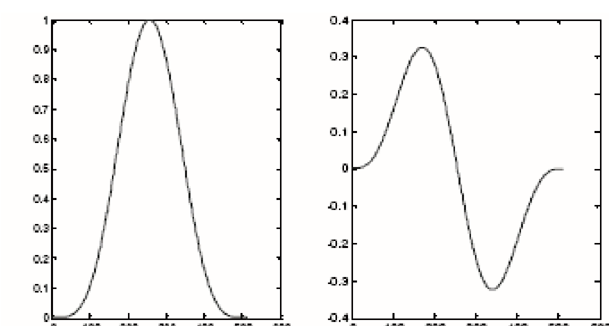

Fig. 1. A smoothing function and its corresponding wavelet.

By correlating the signal with this function at all possible translations and scales a continuous wavelet transform is obtained. According to Mallat, one would need to consider the coefficients across all scales, and determine the positions of the edges of the signal. Edges are characterized by their Lipschitz regularity. It is said that a function is uniformly Lipschitz 'α', over the interval (a,b), if and only if for every x, x_o in the interval, there is some constant K such that,

$$|f(x) - f(x_o)| \le K\,|x - y|^{\alpha} \quad (10)$$

The area over the interval will never have a slope that is steeper than the constant K [7]. Mallat shows that the Lipschitz continuity is related to the wavelet transform, and that if the wavelet transform is Lipschitz 'α' the function is also Lipschitz 'α'.

The algorithm can be extended to 2 – dimensions. It is said that a 2 – D image Lipschitz 'α' in the box $(x_o, y_o) - (x_1, y_2)$ if and only if there is a constant K such that for any two points in the box

$$|f(x,y) - f(x_o, y_0)| \le K(|x - x_o|^2 + |y - y_o|^2)^{\alpha/2} \quad (11)$$

When the wavelet transform of the image is performed, it results in two stacks of images. One stack contains the separable horizontal filtering and the other contains the vertical filtering. The algorithm is performed at all dyadic scaling levels. At each step, the image is convolved with a Gaussian of increasing scale. The modulus maxima image combines the two filtered images, and it is calculated using the formula,

$$M_s f(x,y) = \sqrt{|W_s f(x,y)|^2 + |W_s f(x,y)|^2} \quad (12)$$

The angular image is calculated using,

$$\theta = \arctan\left[\frac{W_s^{\,2} f(x,y)}{W_s^1 f(x,y)}\right] \quad (13)$$

3.1.1 Scales of edges

The scale is not adjustable with classical edge detectors, but with the wavelet model, one can construct edge detector with proper scales. The resolution of an image is directly related to the proper scale for edge detection. High resolution and small scale will result in noisy and discontinuous edges; low resolution and large scale will result in undetected edges. The scale controls the significance of edges to be shown. The significance of an edge can be mathematically measured by Lipschitz exponent.

4.0 EXPERIMENT RESULTS AND ANALYSIS

In this section the wavelet based edge detection algorithm is compared with a variety of classical algorithms for edge detection. Fig. 2 is the original Femur X – ray image. The main reason for using the Roberts Cross operator is that it is very quick to compute. Only four input pixels need to be examined to determine the value of each output pixel, and only subtractions and additions are used in the calculation. In addition there are no parameters to set. Robert's algorithm uses such a small kernel, which is very sensitive to noise. It also produces very weak responses to genuine edges unless they are very sharp. The Sobel operator performs much better in this respect.

The Sobel operator is slower to compute than the Roberts Cross operator, but its larger convolution kernel smoothes the input image to a greater extent and so makes the operator less sensitive to noise. The operator also generally produces considerably higher output values for similar edges, compared with the Roberts Cross. Natural edges in images often lead to lines in the output image that are several pixels wide due to the smoothing effect of the Sobel operator. Some thinning may be desirable to counter this. Failing that, some sort of hysteresis ridge tracking could be used as in the Canny operator.

The effect of the Canny operator is determined by three parameters --- the width of the Gaussian kernel used in the smoothing phase, and the upper and lower thresholds used by the tracker. Increasing the width of the Gaussian kernel reduces the detector's sensitivity to noise, at the expense of losing some of the finer detail in the image. The localization error in the detected edges also increases slightly as the Gaussian width is increased. Usually, the upper tracking threshold can be set quite high, and the lower threshold quite low for good results. Setting the lower threshold too high will cause noisy edges to break up. Setting the upper threshold too low increases the number of spurious and undesirable edge fragments appearing in the output.

The compass edge detector is an appropriate way to estimate the magnitude and orientation of an edge. Although differential gradient edge detection needs a rather time-consuming calculation to estimate the orientation from the magnitudes in the x- and y-directions, the compass edge detection obtains the orientation directly from the kernel with the maximum response. The compass operator is limited to (here) 8 possible orientations; however experience shows that most direct orientation estimates are not much more accurate. On the other hand, the compass operator needs (here) 8 convolutions for each pixel, whereas the gradient operator needs only 2, one kernel being sensitive to edges in the vertical direction and one to the horizontal direction.

The behavior of the Laplacian of Gaussian zero crossing edge detector is largely governed by the standard deviation of the Gaussian used in the Laplacian of Gaussian filter. The higher this value is set, the smaller features will be smoothed out of existence, and hence fewer zero crossings will be produced. Hence, this parameter can be set to remove unwanted detail or noise as desired. The idea that at different smoothing levels different sized features become prominent is referred to as `scale'. All edges detected by the zero crossing detector are in the form of closed curves in the same way that contour lines on a map are always closed. The only exception to this is where the curve goes off the edge of the image. Since the Laplacian of Gaussian filter is calculating a second derivative of the image, it is quite susceptible to noise, particularly if the standard deviation of the smoothing Gaussian is small. Thus it is common to see lots of spurious edges detected away from any obvious edges. One solution to this is to increase the smoothing of the Gaussian to preserve only strong edges. Another is to look at the gradient of the Laplacian of Gaussian at the zero crossing (*i.e.* the third derivative of the original image) and only keep zero crossings where this is above a certain threshold. This will tend to retain only the stronger edges, but it is sensitive to noise, since the third derivative will greatly amplify any high frequency noise in the image.

With the wavelet model, one can construct edge detector with proper scales. The resolution of an image is directly related to the proper scale for edge detection. High resolution and small scale will result in noisy and discontinuous edges; low resolution and large scale will result in undetected edges. The scale controls the significance of edges to be shown. Edges of higher significance are more likely to be kept by the wavelet transform across scales. Edges of lower significance are more likely to disappear when the scale increases. The significance of an edge can be mathematically measured by Lipschitz exponent. Wavelet filters of large scales are more effective for removing noise, but at the same time increase the uncertainty of the location of edges. Wavelet filters of small scales preserve the exact location of edges, but cannot distinguish between noise and real edges.

Fig.2. Original Input image

Results of edge detection using classical edge detectors are shown in Fig.2 to Fig.5. Also results of wavelet based edge detection are with different scale are shown in Fig. 6 and Fig.7.

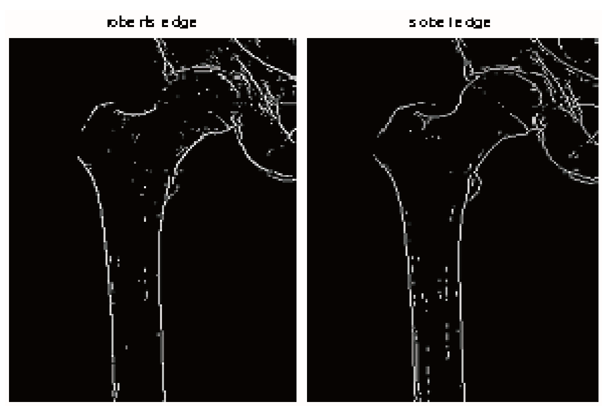

Fig.3. Robert's edge and Sobel's edge

Fig.4. Prewitt's edge and zero cross LoG edge

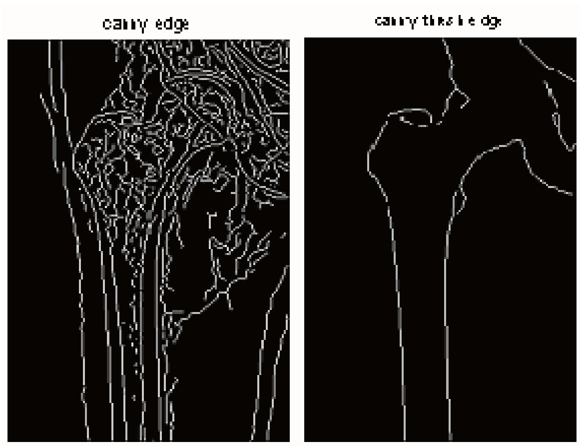

Fig.5. Canny's edge and Canny's threshold edge

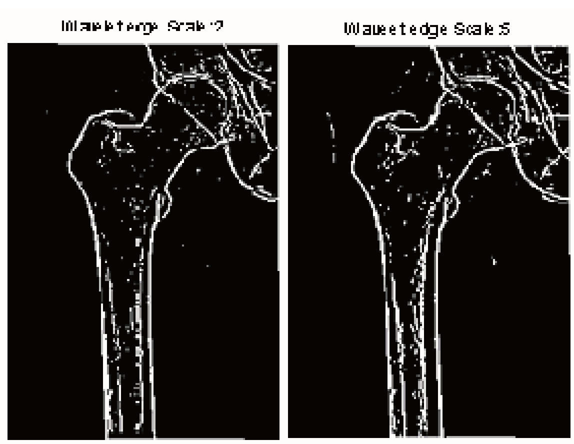

Fig.6. Wavelet edge Scale: 2 and 5

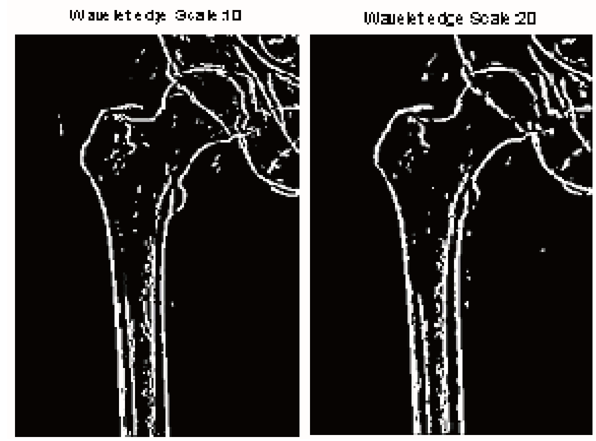

Fig.7. Wavelet edge Scale: 10 and 20

5.0 CONCLUSION

In this paper, a simulation work have been carried out to estimate the performance of classical edge detection algorithms on femur bone extracted from hips X – ray image. A new approach for edge detection using wavelet transforms is investigated for femur bone, which yields the remarkable performance improvement compared to classical algorithms. In the reported work, initially some major classical edge detectors are reviewed and interpreted with continuous wavelet transforms. The classical edge detectors work fine with high-quality pictures, but often are not good enough for noisy pictures because they cannot distinguish edges of different significance. The wavelet based edge detection algorithm combines the coefficients of wavelet transforms on a series of scales and thus improves the detection significantly. It has been also observed that on incorporating use of multi scale wavelet transform further results in improved performance.

REFERENCES

[1] J.C Goswamy, A.K Chan, 1999, "Fundamentals of Wavelets: Theory, algorithms and applications," John Wiley & sons, Inc.

[2] R.C.Gonzalez, R.E.Woods, 1993, "Digital image processing", Addison - Wesley publishing company, Inc .

[3] S.Mallat, S.Zhong, 1992, "Characterization of signals from mutiscale edges", IEEE transactions on pattern analysis, machine intelligence, vol.14,no.7,pp 710 - 732.

[4] S.Mallat, W>LHwang,1992,"Singularity detection and processing with wavelets," IEEE transactions on information theory, vol.38,no.2,pp 617 - 643..

[5] I.Daubechies,1992, "Ten lectures on wavelets," CBMS – NSF series in Appl.Math., #61,SIAM Philadelphia.

[6] S.Mallat," Awavelet tour of signal processing", Academic press, san diego, 1998. .

[7] Wikipedia"Lipschitzcontinuity",http://en.wikipedia.org/wiki/ Lipschitz_continuity.

[8] Chen, Y., Ee, X., Leow, W.K., Howe, T.S.: Automatic extraction of femur contours from hip x-ray images. In: Proc. ICCV Workshop on Computer Vision for Biomedical Image Applications, pp. 200–209 (2005).