

Diagnosis of X-Ray Using Gabor Wavelet Transform

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ABSTRACT

The bone fracture is common problem in human beings due to accident or other causes like bone cancer etc. The fracture can occur in any bone of our body like wrist, heel, ankle, hip, rib, leg, chest etc. It is not possible to view fractures by naked eyes, so X-ray/CT images are used to detect it. But sometimes these images lack sufficient details needed to diagnose. Now a day's image processing is playing an important role in bone fracture detection. Image processing is important in modern data storage and data transmission especially in progressive transmission of images, video coding (teleconferencing), digital libraries, image database, and remote sensing. This paper presents a study of image processing techniques for bone fracture detection. This paper will help user to study different methods for bone fracture detection using image processing and to design new techniques to improve accuracy of fracture detection. Wavelets have been widely used in signal and image processing. Wavelet transforms have been successfully applied to many topics including tomography reconstruction, image compression, noise reduction, image enhancement, texture analysis, segmentation, multiscale registration. This paper also presents technologies used to implement image processing based system for fracture detection with pros and cons.

Keywords: X-rays, CT Images, Tomography.

I. INTRODUCTION

The facture can be defined as crack in bone or break in a bone. Proteins, fibres and minerals form a bone of our body. Number of bones are joined together to form a skeleton of the body. Support to the body shape, protection to the organ of body is provided by skeleton. Bones helped to produce red blood cells. With help of bones we can run, jump, kneel, and lift. Bones also protect our internal organs from the damage. Various shape, size and structure of bone occur in human body. Femur bones are the largest bones and auditory bones are the smallest bones. Different types of bone occurs as oblique, compound, spiral, greenstick and important. X-rays and detection combined to walk, seat, fractures transverse. To identify such a different types bone fractures different medical imaging tools are used such as X-rays, CT (computed tomography) images, MRI (Magnetic Resonance Imaging), ultrasonic, etc. Most commonly used technique are X images in fracture detection. These techniques provide easiest way to diagnosis. For existence and location of fracture, doctors usually use X-rays, broken bones are very common.

In X-rays, there are three types of different intensities can be occur such as background, bones, and fractured region in region we can identified the fracture region using pixel classifications. In this section we can determine the actual length of the fracture. The calculated result will be applied with fuzzy logics. To apply fuzzy logics there are different fuzzy rules by which we can calculate the actual result. The obtained result will be analysed with the previous observations. In this way we can obtain the different result for different images as input taken into considerations. Wavelet transforms and other multi-scale analysis functions have been used for compact signal and image representations in de-noising, compression and feature detection processing problems for about twenty years. Numerous research works have proven that space-frequency and space-scale expansions with this family of analysis functions provided a very efficient framework for signal or image data. The wavelet transform itself offers great design flexibility.

We will introduce the wavelet multi-scale analysis framework and summarize related research work in this area and describe recent state-of-the-art techniques.





Figure 1. Block diagram

The X-Rays /CT images are obtained from the hospital that contains normal as well as fractured bone images. In the first step applying pre-processing techniques such as RGB to gray scale conversion. The image enhancement can be obtained by removing noise from the image. Then image classification can be done so as to separate background, ROI (region of interest) and infected pixels. Then infected pixels get marked. Then this images will be compared with the given data base and result is calculated by applying fuzzy logic to it.

Image pre- processing usually consists of an application-dependent technique for enhancing preselected features or for removing irrelevant detail. Most image processing techniques which have been applied to biomedical situations have been found to be very application dependent. The pre-processing

techniques are designed to enhance selected features and eliminate irrelevant data. The feature extraction techniques are designed to extract specified, application-dependent information from a digitalized radiographic image. In this paper for pre-processing Gabor wavelet transform is used. The detail of Gabor wavelet transform is given as follows.

Fundamentals of Gabor wavelet transform:

The Fourier transform has been the most commonly used tool for analyzing frequency properties of a given signal, while after transformation, the information about time is lost and it's hard to tell where a certain frequency occurs. To solve this problem, we can use kinds of time-frequency analysis techniques learned from the course [3] to represent a 1-D signal in time and frequency simultaneously. There is always uncertainty between the time and the frequency resolution of the window function used in this analysis since it is well know that when the time duration get larger, the bandwidth becomes smaller. Several ways have been proposed to find the uncertainty bound, and the most common one is the multiple of the standard deviations on time and frequency domain:

 $\sigma t^{2} = t^{2}|(t)|^{2}dt |x(t)|^{2}dt, \sigma f^{2} = f^{2}|X(f)|^{2}df |X(f)|^{2}df$ (1) $\sigma t \times \sigma f \ge 14\pi$ (2)

Among all kinds of window functions, the Gabor function is proved to achieve the lower bound and performs the best analytical resolution in the joint domain [4]. This function is a Gaussian modulated by a sinusoidal signal and shown below:

 $\varphi t = exp[iii](-\alpha 2t2)exp[iii](j2\pi f0t)$ (3) $\Phi f = \pi \alpha 2exp[iii](-\pi 2/\alpha 2(f-f_0)2)$ (4)

Where α determines the sharpness and f0 the is modulated center frequency of , and Φf is its Fourier transform. Fig.1 shows the example of φt with three different f0 but the same α and their time-frequency analysis by Gabor transform. These three distributions have the same area but don't meet the multiresolution requirement: the window size should depend on the center frequency. To achieve this requirement, we substitute a with $f0/\gamma$, where γ is an self-defined constant, and make the time duration of φt dependent on the central frequency f0. The generalized φt with normalization of the maximum response in frequency domain is now defined as:

 $\varphi t = |f0| \gamma \pi \exp^{it0}(f02\gamma 2t2) exp^{it0}(j2\pi f0t)$ (5)

Fig.2 shows the example of this new-defined φt with three different f0 but the same α and their time-frequency analysis by Gabor transform.



Figure 2. Example of φt with three different f0=0,0.5, and 1 but the same $\alpha=0.5$ and their time-frequency analysis by Gabor transform, where (a)-(c) show the real part of φt and (d)-(f) show the magnitude of the Gabor transform of φt .

This 1-D Gabor function could be extended into 2-D form and also achieve the lower bound of uncertainty principle [5]. This 2-D Gabor function is defined as [2]:

$$\varphi x$$
, = $f2\pi\gamma\eta exp$ (-($f2\gamma 2xr2+f2\eta 2yr2$)) exp ($j2\pi fxr$)
(6) $xr=xcos\theta+ysin\theta, yr=-xsin\theta+ycos\theta$

where *f* is the frequency of the modulating sinusoidal plane wave and θ is the orientation of the major axis of the elliptical Gaussian. The 2-D Fourier transform of φx , is shown below:

 $\Phi u, = exp^{[iii]}(-\pi 2(\gamma 2f2 \quad ur-f \quad 2+\eta 2f2vr))$ (7) $ur=ucos\theta+vsin\theta, vr=-usin\theta+vcos\theta$

In practical cases, the Gabor wavelet is used as the discrete wavelet transform with either continuous or discrete input signal, while there is an intrinsic disadvantage of the Gabor wavelets which makes this discrete case beyond the discrete wavelet constraints: the 1-D and 2-D Gabor wavelets do not have orthonormal bases. If a set of wavelets has orthonormal bases, the inverse transform could be easily reconstructed by a linear superposition, and we say this wavelet transform provides a complete representation. The nonorthonormal wavelets could

$$MSE = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - y(i,j))^2}{MN}$$

provide a complete representation only when they form a frame [1]. The concepts of the frame is beyond the scope of this report because it's too theoretical, while in most of the applications, we don't really care about these nonorthonormal properties if the Gabor wavelets are used for feature extractions. When extracting features for pattern recognition, retrieval, or computer vision purpose, the transformed coefficients are used for distance measure or compressed representation but not for reconstruction, so the orthogonal constraint could be omitted.

$$NC = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) * y(i,j))}{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j))^{2}}$$

III. ANALYSIS

A. Analysis with respect to PSNR value, MSE, NC and Time Constraint

$$AD = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j) - y(i,j))$$

Peak signal-to-noise ratio (PSNR): It is an expression for the ratio between the maximum possible value (power) of a signal and the power of distorting noise that affects the quality of its representation. Because many signals have a very wide dynamic range, (ratio between the largest and smallest possible values of a changeable quantity) the PSNR is usually expressed in terms of the logarithmic decibel scale. PSNR is most commonly used to measure the quality of reconstruction of lossy compression codecs. The signal in this case is the original data, and the noise is the error introduced by compression. When comparing compression codecs, **PSNR** is an approximation to human perception of reconstruction quality. Although a higher PSNR generally indicates that the reconstruction is of higher quality, in some cases it may not be. One has to be extremely careful with the range of validity of this image; it is only conclusively valid when it is used to compare results from the same codec (or codec type)and same content PSNR can be calculated as, PSNR=10 log 255²

Mean Square Error (MSE): It measures the average of the square of the error. The error is the amount by which the pixel value of original image differs from the pixel value of decrypted image.

Normalized Correlation (NC): It measures the similarity representation between the original image and decrypted image.

B. Analysis with respect to AD value, MD, NAE and SC:

Average Difference (AD): Average Difference is measurement of differences between two images. Here we calculated the average difference by the formula given. As we know that large value of maximum difference means that image is poor in quality.

Maximum Difference (MD): Difference between any two pixels such that the larger pixel appears after the smallest pixel. As we know that large value of

maximum difference means that image is poor in quality. MD is defined as.

MD = MAX |x(i, j) - y(I, j)|

$$NAE = \frac{\sum_{m=1}^{M} \sum_{n=1}^{N} |x(m,n) - y(m,n)|}{\sum_{m=1}^{M} \sum_{n=1}^{N} |x(m,n)|}$$

Normalized Absolute Error (NAE): The large value of normalized absolute error means that image is poor quality. NAE is defined as

Structural Content (SC): The structural content measure used to compare two images in a number of small image patches the images have in common. The patches to be compared are chosen using 2D continuous wavelet which acts as a low level corner detector. As we know that large value of structural content SC means that image is poor quality. SC is defined as,

$$SC = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (y(i,j))^{2}}{\sum_{i=1}^{M} \sum_{j=1}^{N} (x(i,j))^{2}}$$

IV. RESULT

The graphical user interface will be appearing as shown in fig a. It consist of various blocks such as menu, infected region and analysis section. The input image will be displayed as shown in fig b. This input image need to pre-process so as to remove the noise and enhance the features of image. The pre-process image will be appearing as shown in fig c. The region of interest will be found by applying different algorithm to it and then fractured area will crop as shown in fig e. If the pattern of fracture image is not same then it will be added to the database. The result analysis will be obtained as shown in figure f.

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Figure 3g. Result Analysis

V. CONCLUSION

A computer based analysis techniques for the detection of bone fracture using X-ray images has been presented in this work. It starts from the preprocessing to remove the noise and enhancing brightness of the image by using the Gabor wavelet transform the pixelization of the image is done. Segmentation will be done and we get the expected outcomes. This system also can be used for eye image diagnosis and MRI images too.

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