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Bone Fracture Detection using X-ray Images

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***Abstract**: Diagnosing minute fractures in the cases of pelvis bone injuries is critical for speedy and successful patient treatment. Minute fracture detection using x-ray images can be challenging and time consuming to examine due to their low resolution and dissimilar visual characteristics of fractures by their position. The pelvis bone is most dense due to which visual detection of the fracture is very difficult. This paper presents a fracture detection technique for the pelvis bone as well as pubic ring using Distance Regularized Level Set Evolution (DRLSE) technique for segmentation and detection of fracture using Canny Edge detector and gradient technique. Also inspection of displacement of the pelvic bone is done using Gray Level Co-occurrence Matrix (GLCM). Results so far have been encouraging and will be helpful in guiding the physicians and for better treatment of the patients.*

***Index Terms**: Biomedical image processing, Distance regularized level set evolution, Image processing, Pelvis bone fracture.*

I. INTRODUCTION

Pelvic fractures are very traumatic and studies reveal that the mortality rate of the patients with pelvic fracture is up to 55% [1]. Traumatic injuries in pelvic region can result in grievous hemorrhage, multiple nerve injuries, organ dysfunction, and internal organ damage. Even if injuries of this intensity does not occur, acute pain and impaired mobility are usually bound with pelvic fractures. Faster and accurate diagnosis is necessary for patient's survival. But, highly dense and complex bone structure makes diagnosis challenging in intense situations. There has been development in biomedical image processing to assist the physicians in many biomedical fields, but so far research in image processing techniques to diagnose fractures especially in pelvic region is barely done. Biomedical image processing techniques on x-ray image is also a challenge due to its high inhomogeneity, noise and varying intensity. Moreover, pelvis bone x-ray images are rare and images collected are not stored for future references in the hospitals. Furthermore, physicians prefer higher and more costly imaging techniques in the cases where the fracture is not confidently diagnosed. Therefore it becomes a necessity to provide better image processing techniques that can be cost efficient as well as accurate to help the physicians for better treatment.

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This work focuses on extracting information from the x-ray images, detection of fracture in the pelvic bone and pubic bone and judgement of the displacement of the pelvis. X-ray images are used as forefront diagnostic technique due to its faster availability and low cost. However image noise, complexity in pelvis bone structure and inhomogeneity makes it difficult to find minute fractures thus consuming time. Discussions with medical experts reveal difficulty at times in detecting fractures. A system that can help the physicians will thus save time and help them in decision making.

Fracture detection using x-ray images is an under-explored field. There are studies that detect fractures in bones such as arm, femur, leg, skull, joints etc. [2]-[6]. Research on detection of different types of fractures such as transverse fractures, open fractures, simple fractures, spiral fractures, commuted fractures etc. have also been done in past [7]. However, studies on pelvis bone, which is in fact an area which does not form clear image using x-rays is very rare. Also many studies have been badly suffered due to lack of proper database. Pelvis bone x-ray database with similar visual characteristic is also very rare. There has been least research to detect fractures in the pelvic bone according to our study [8], [9], [10]. Researches done in past on pelvic bone fracture detection include using of Active Shape Model (ASM) for segmentation of the bone [10]. ASM has been widely used for many biomedical image processing researches since it occupies the desired shape of the object automatically for segmentation. The idea of ASM is derived from Active Contour Algorithm, which is the basic form, widely used for segmentation [11]. It is the means of matching the deformable model to an object in the image. Fractures detection includes techniques such as Sobel operator and canny edge detection as described in [3], [5], [10]. Features extracted in many biomedical image processing are done by Gray Level Co-occurrence Matrix (GLCM) [3], which is widely used.

Our method is based on DRLSE segmentation of the pubic ring [12], canny edge detection to detect fractures in the pubic ring and also feature extraction for the assessment of the displacement in the bone using GLCM technique as shown in figure 1. Gradient of the image is also used to localize fractures in the pubic bones as well as pelvic bones. Each step will be properly explained in the following sections.

II. SEGMENTATION

Fracture detection is affected extremely due to varying visual characteristics of the radiograph. It is important to segment the desired portion for effective fracture detection. Previous work have focused on using Contour models to segment biomedical images [10], [11] and Chapter 2 in [13]. Active contour models are capable of.

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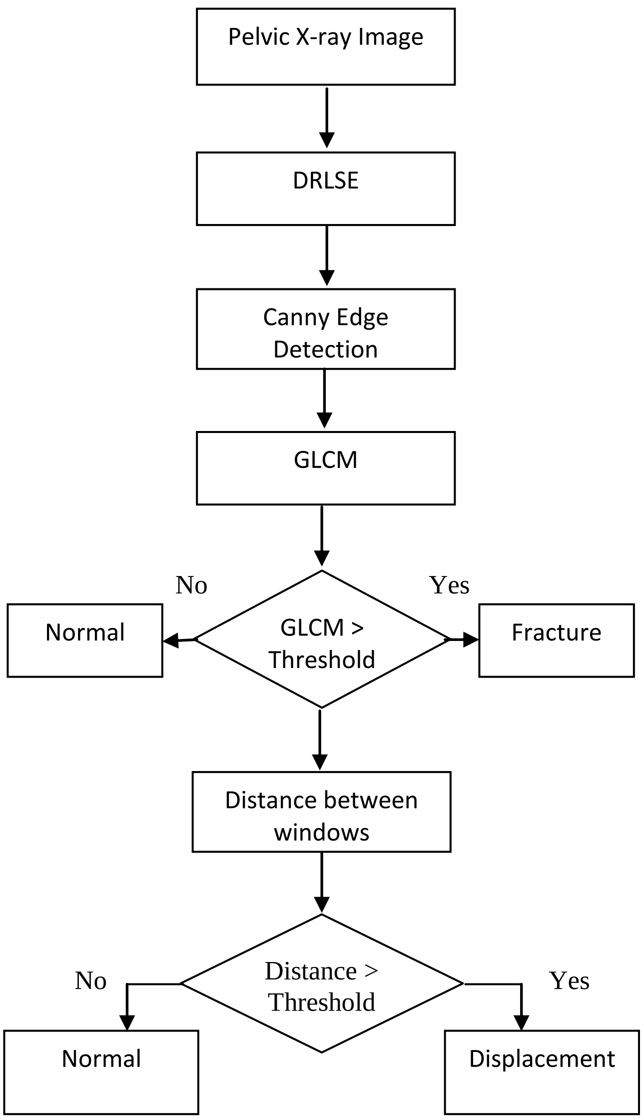

Fig. 1 Outline of Detection Process in Pubis

Accommodating a wide range of shape variability over time and space in a geometrically constrained framework, as explained in Chapter 2 in [13]. This geometric constraint imparts a compact form of shape information.

This paper focuses on the use of Distance Regularized Level Set Evolution (DRLSE) [12] for segmentation, which is a new variational level set formulation in which the regularity of the level set function is intrinsically maintained during the level set evolution. Conventional level set evolutions create irregularities during its evolution. Therefore re-initialization is done to avoid irregularities using a signed distance function. However re-initialization degrades the numerical accuracy. Thus due to this problem a self-regularizing level set method is considered , which would regularize the level set function during the evolution stage without re-initializing the level set function.

The DRLSE is a gradient flow method, which is based on the energy function, which minimizes due to the convergence of the solution.

In order to analyze this method, the gradient flow algorithms are to be discussed as a prerequisite.

The gradient flow or the gradient descent algorithm starts with an idea of developing a curve that would minimize the function '*f*', whose derivative exists or can be approximated. The Level Set Evolution is a gradient flow method in which the energy functional must be minimized using the distance regularization term along with another external energy functional, which would drive the function towards the solution location.

The initialization stage comprises of the template creation stage, which would be used for template matching in the later stages by the use of particle filter framework. The DRLSE introduced in [12] has been used for the segmentation of the initial templates. The level set evolution is deduced as an inclination stream that minimizes the energy useful with a distance regularized term and an external energy that drives the zero level set towards the homogeneous segment areas. The distance regularization term is characterized with a potential capacity such that the determined level set evolution has one kind of Forward-and-Reverse dispersion impact, which can keep up a desired state of the level set capacity, especially a marked separation profile close to the zero level set. This produces different sort of level set advancement named as DRLSE. The distance regularization impact eradicates the requirement for re-initialization and consequently maintains a strategic distance from its affected numerical mistakes. The energy functional $\varepsilon(\phi)$ of the LSF ϕ in the domain Ω is given by,

$$\varepsilon(\phi) = \mu R_p(\phi) + \varepsilon_{ext}(\phi) \qquad (1)$$

where R_p is the distance regularized term defined as,

$$R_p \triangleq \int_\Omega p(|\nabla \phi|)dx \qquad (2)$$

where p is the potential energy density function and $\varepsilon_{ext}(\phi)$ is the external energy function which is dependent on the data of interest, which is the image in the proposed implementation.

As opposed to cofounded implementations of usual level set plans, a less difficult and more effective limited contrast plan can be utilized to realize the DRLSE detailing. DRLSE likewise permits utilization of more broad and proficient introduction of the level set capacity. In its numerical usage, moderately vast time steps can be utilized as a part of the limited distinction plan to decrease the quantity of emphasis, while guaranteeing adequate numerical accuracy.

The DRLSE is applied on both the pubic rings separately. Since there are wide variations in the structure, size and direction in the viewing angles in different x-ray images of the patients, the seed points for initial LSF in the pelvic ring as well as pubic cannot be maintained constant. So we develop an algorithm wherein the user can point the cursor at the location where the initial LSF is required to be generated. The DRLSE expands up to the pubic rings and takes the shape of the rings. Higher energy is required to advance the Level Set Function (LSF) towards higher intensity change. Since the energy is maintained low, the (LSF) stops at the boundary of the bone which is of a higher intensity than the background.

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The segmentation process of left pubic ring and the right pubic ring are shown in figure 2(a) and 2(b) respectively.

(a)

(b)

Fig. 2 Segmentation Process Output of Left and Right Pubic Ring

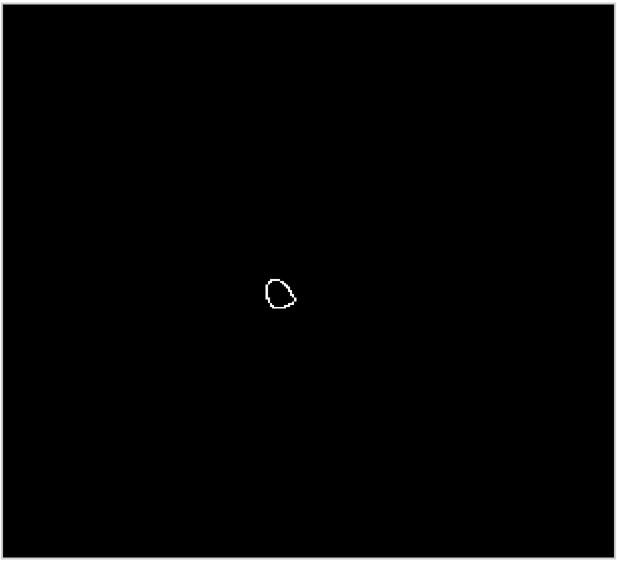
III. Edge Detection

Edge detection is necessary to detect the edges in the segmented image. We have used Canny edge detector to detect the edges of the pubic ring. It is the most popular technique for the detection of edges with low error rate and minimal false edges using reduced amount of data. Figure 3(a) and 3(b) show the results of Canny edge detection of left pubic ring and right pubic ring respectively.

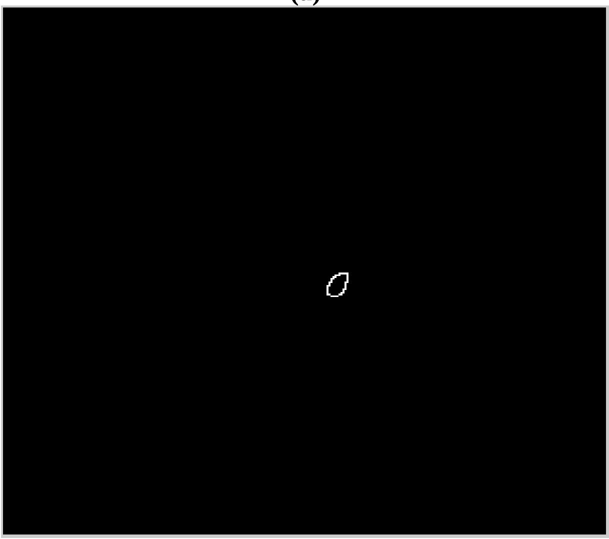
IV. FEATURE EXTRACTION

Feature extraction is an important step in many image processing applications. Gray-Level Co-occurrence Matrix (GLCM) is used for feature extraction. GLCM is an important tool used in image texture analysis. Textures of an image are complicated visual patterns comprised of objects or regions with sub-patterns having characteristics like color, size, brightness, shape etc. It shows image texture structure by statistically sampling the patterns of gray levels arising in relation to other gray levels.

Depending upon the GLCM values, it will be determined whether the pubic rings have fractures or not. We have compared the GLCM values of the right pubis and the left pubis for co-occurrences. If it is greater than the threshold, which is greater than 300 in our research, the bones are considered to be fractured.



(a)



(b)

Fig. 3 Edge Detection of Left and Right Pubic Ring

V. DETERMINING DISPLACEMENT

Pelvic bones are compromised to being displaced from its original position along with having fractures. This results in severe pain and therefore should be diagnosed properly and quickly.

The pubic bone is a part of the pelvis. Therefore we determine whether there is a displacement in the pubic bones, and hence determining whether there is a displacement in the pelvis.

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This is done by finding the minimum or the first row in the image matrix of the segmented outputs of the right and the left pubic rings. By comparing the difference in distance between the first rows of both the right and left pubic rings, after the edges are detected by the canny edge detector, we can determine whether there is a displacement in the pelvis or not. If the displacement incurred is more than threshold value 30 in our database, then the pelvis is diagnosed to be displaced.

VI. LOCALIZATION OF FRACTURE

Finding maximum gradient is the localization principle used in this implementation for fracture localization.

The gradient is found in all the three levels of the RGB image. That gradient is calculated in all the red, green and blue layers of the image and is checked for variation in the gradient in all the three layers. The crack region would have a deepest gradient. The presence of this gradient will determine whether there is a crack on the bone or not. Thus by using this geometrical constraint, the decision making is carried out and the results are obtained. The gradient is calculated by using convolution kernels given by,

$$G_x = [-1 \;\; 1] \quad G_y = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \tag{3}$$

Localization of the fracture is done by taking intercept values in X and Y directions and by masking the crack with a rectangle.

VII. RESULTS

The database was provided by Healthway hospital. A total of 21 pelvis x-ray images have been taken of the patients upon their arrival at the hospital. Some images after the surgery or internal fixation are also included. All the images were resized to a standard width and height of 300 pixels each. Out of the total images, 18 images were normal and the rest were having some defects. The results were discussed with the experts and they suggest a good accuracy of 85.71%.

Fig. 4 Detection and Localization of Fracture in The Bone

Our database contained very few images of pelvic and pubic fractures, as patients can suffer fractures in other bones. Better assessment will be done with more x-ray images. The same is true for detecting displacement.

VIII. CONCLUSION

This paper presents a method to detect fractures in the pubic ring in x-ray images using Distance Regularized Level Set Evolution and then gathering the features from the edges obtained by Canny edge detection technique. Fractures in the bone is also detected using gradient method. Further, displacement of the pubis is also determined. The results are promising so far, having been tested for three cases (normal, fracture, displacement). The results and techniques use in this research is better as compared to [9] and [10]. Once the approach is verified with more data, the proposed method will be very effective for larger systems in computer-aided evaluation making system.

Future work will involve testing with larger database of x-ray images. Further systems can be developed to detect the fractures in the pubic ring without having the need to insert seed points manually for each image. Geometrical analysis of the features extracted from the pelvic ring can also be compared with the normal bone to determine whether there is a fracture or not. Also, the classification of the severity of the fractures can be done in future.

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