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Enhanced Automatic X-Ray Bone Image Segmentation using Wavelets and Morphological Operators

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Abstract. X-ray bone segmentation is a vital step in X-Ray image analysis techniques. the main aim of segmentation is to subdivide the various portions, so that it can help medical practitioners (i) During the study of bone structure, (ii) Identification of bone fracture, (iii) Measurement of fracture treatment, (iv) Treatment planning prior to surgery. It is considered as a challenging task because the bone x-ray images are complex in nature and the output of segmentation algorithm is affected due to various factors like partial volume effect, intensity inhomogeneity, presence of noise and artifacts and Closeness in gray level of different soft tissues

Keywords: X-Ray Bone Segmentation, Long Bone, Tibia, Wavelets, Morphological Operators.

1. Introduction

Digital images are increasingly used by medical practitioners to help them during disease diagnosis. These images display various body organs and are used during treatment decision making process. The images are produced by several state-of-the-art medical equipments like MRI, CT, ultrasound and X-Ray. Out of these, X-Ray is one the oldest and frequently used devices, as they are non-intrusive, painless and economical. The X-Ray images are used during various stages of treatment which include fracture diagnosis and treatment, evaluation of skeletal maturation and bone densitometry.

X-Ray image analysis techniques to access bone content and bone structure is an area of research that has attracted many researchers [9, 12, 2]. Almost all these techniques, extract features from x-ray images for bone analysis. One important a sub-field of image analysis is the segmentation of bone structure from the x-ray image. Image segmentation is used to classify or assign each pixels into a group (label), where each group represent membership to a set of pixels that define an object or region in the image. Thus, the main aim of segmentation is to subdivide the various portions, so that it can help medical practitioners (i) During the study of bone structure, (ii) Identification of bone fracture, (iii) Measurement of fracture treatment, (iv) treatment planning prior to surgery. It is considered as a challenging task because the bone x-ray images are complex in nature and the output of segmentation algorithm is affected due to various factors like partial volume effect, intensity in homogeneity, presence of noise and artifacts and Closeness in gray level of different soft tissues.

The solutions proposed can be categorized into two main groups, namely, gray level feature-based methods and texture feature-based methods. Gray level feature-based methods analyze the gray level or color features of an image to segment an image. Histogram-based methods [01], Edge-based methods [3], region-based methods [13] all belong to this category. Histogram-based methods are the simplest and work with a threshold value. The result of segmentation depends on the correct selection of threshold, which often is difficult. The performance of these methods often degrades in the presence of noise. The edge-based methods works well for noise-free images, but its performance degrades with noisy images or when fake or weak edges are present in the image.

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Better results could be obtained when it is combined with a region-based algorithm. Watershed algorithm for segmentation is an area of region-based segmentation which has received more attention [6, 7]. While using region based segmentation, both over and under segmentation of regions in the image might occur and careful handling of segmentation process to avoid these situations are needed.

Textural features of an image are considered important from both segmentation and classification point of view. The aim here is to divide images into regions with similar texture properties [8]. All these methods use random patterns/textures but work well for segmenting medical images. Apart from these, model based segmentation and Atlas based segmentation techniques have also been proposed. Model based methods involve active shape and appearance model during training. They work by determining and analyzing the statistical influence between the model and image during segmentation. These methods often require manual interaction and exhibits poor convergence to concave boundaries [9].

Atlas based approaches are powerful approaches for image segmentation. In this, information on anatomy, shape, size, and features of different, organs, soft tissues is compiled in the form of atlas or look up table (LUT). Atlas guided approaches are similar to co-relation approaches and the plus point of atlas based approaches is - it performs segmentation and classification in one go. Atlas based segmentation approaches are among the third-generation algorithms. There are indications that certain atlas based methods can compete with manual segmentations although atlas selection, atlas registration procedure, and the manual tracing protocol used in atlas formation are factors that can affect performance [15]. However, they face limitations in segmenting complex structure with variable shape, size, and properties and moreover, expert knowledge is required in building the database.

All these methods work on a common objective, that is, to provide solution for efficient automatic medical image segmentation. Although a number of algorithms have been proposed to solve the problem of segmentation in x-ray images, it is still considered complex and challenging. Recently the use of morphological transformation and wavelet transformation are gaining more attention for segmenting medical images. In wavelet based techniques the result of wavelet transform is used as features during segmentation. Morphological transformation combines geometrical features and edge features to segment the image. Use of morphological-based segmentation helps to avoid the problem of over and under segmentation [5]. The advantage of using wavelet transform is that it provides a precise and unifying framework for the analysis and characterization of an image at different scales. This advantage can be fully exploited for efficient segmentation of X-Ray images. Further, the use of wavelets increases the speed of the segmentation and reduces the number of computations performed by selecting only the prominent pixels within an image [1].

Santhaiah *et al.* [11] proposed a morphological based segmentation method for segmenting medical images. The results of the method proposed used morphological transformation operations, dilation and erosion, during segmentation. A gradient analysis was initially conducted to determine the edges, which were then used as input to subsequent dilation of eroded image. The results proved that segmentation was efficient and was able to preserve important edges of the bone X-Ray images. However, while provided with large pictures, the algorithm was little slow because of the various computation involved. Further, preserving edges of a bone image is very important, as they are used by the subsequent steps of image analysis, like fracture detection. Therefore, the main aim was to preserve edges while segmenting the bone image. Fro this purpose, this paper proposes to enhance this algorithm by combining it with wavelet transformation.

The rest of the paper is organized as follows: Section 2 discusses the concept behind wavelet transform. Section 3 discusses the enhanced proposed system. Section 4 presents the results obtained during various experimentations, while Section 5 concludes the work with future research directions.

2. Wavelet Transformation-Based Segmentation

This section describes the technique of wavelet transform for features extraction associated with individual bone image pixels. For the image decomposition and feature extraction the Haar transform has been applied.

Texture of an image can be defined as a characteristic that has spatial distribution of gray levels in a neighborhood. Texture in an image region is considered similar or constant if its local properties are constant and has the tendency of slow change and are approximately periodic. The segmentation is performed by identification of features that differentiate these textures in the one image. The segmentation process is performed by a simple comparison of the composition operators-occurrence matrix features, contrast and energy of size N x N, obtained using wavelet transforms of sub-band of size 4 x 4, both horizontally and vertically.

The Discrete Wavelet transform used is the most frequently used 1-level decomposition Haar transform. These are generated from a single function by its dilations and translations. The Haar transform results in four sub-bands, namely Low-Low, High-High, High-Low and Low-High. The Low-Low region has most of the energy, while High-High has the least energy. The High-Low and Low-High sub-bands contain the edge details. The composition operators-occurrence matrix features, energy and contrast, is calculated for each sub-band using Equation (1) and (2)

$$\text{Energy} = \sum_{i,j=1}^{N} C_{i,j}^{21} \quad (1) \qquad \text{Contrast} = \sum_{i,j=1}^{N} (i-j)^2 C_{i,j} \quad (2)$$

The results form a new feature matrix. From this, a new difference pixel matrix is constructed by calculating the difference between the value of horizontal and vertical directions. Then the segmentation band is formed across the texture boundaries. At this stage, artifact or spurious spots may appear. These are removed using a simple circular averaging filter. This method convolves the image with a uniform circular averaging filter whose size is the artifact diameter entered. After this the image is reconstructed.

A threshold value is calculated using Otsu's method [14] using which the enhanced image is processed. A skeletonization process is used, where the thick edges are cleaned by removing isolated pixels and removing isolated boundary pixels. Care was taken make sure that the image is not broken apart while removing pixels.

3. Proposed Segmentation Algorithm

The proposed method starts with the 1-level Haar wavelet transformation. To the transformed subbands, the mathematical morphology operators are applied. The operations include dilation (Equation 3), erosion (Equation 4), opening (Equation 5) and closing (Equation 5). In general, dilation expands the object to the closest pixels of the neighborhood, while erosion shrinks the object. Open operation smoothes the images by cutting down a peak, while close operation smoothes it by filling up the valleys.

$$X = E \,\Theta B = \{ x : B(x) < E \} \quad (5)$$

$$Y = E \oplus B = \{ y : B(y) \cap E \neq \varnothing \} \quad (6)$$

$$E \circ B = (E \,\Theta\, B) \oplus B \quad (7)$$

$$E \bullet B = (E \oplus B) \,\Theta\, B \quad (8)$$

where E is the binary image and B is the structuring element. The dilation $\oplus$ combines two sets using vector addition. The erosion Θ combines two sets using vector subtraction of set of elements and is the dual operator of dilation. If the central value of the kernel is less than 'n' then dilation is performed else erosion is performed. Usage of mathematical operations for segmentation eliminates small objects and enhances the connectivity of objects, thus generating an image with areas that have elements with only connected regions.

4. Results

The proposed system was tested using an experimental set consisting of bone X-ray images of 256 x 256 size. In order to quantify the performance of the proposed segmentation method, validation experiments are necessary. Validation is typically performed using one of two different types of truth models. The most straightforward approach to validation is by comparing the automated segmentations with an existing segmentation model. The experimental results are discussed in the following headings (i) Segmentation Result and (ii) Time Taken for Segmentation.

The proposed system was tested with various long bone leg images. The results obtained for four randomly selected images (Figure 1) are presented in this section.

(a) Bone1 (b) Bone2 (c) Bone3 (d) Bone4

Figure 1 : Test Images

4.1. Segmentation Results

The main objective of this research work is to develop a novel algorithm for segmenting medical images. As each medical image have different characteristics, using the same segmentation technique for all types of images is impossible. The present method is developed for X-ray long bone images, but the same can be tested for other images also. Figure 2 shows the result of segmentation on the test images

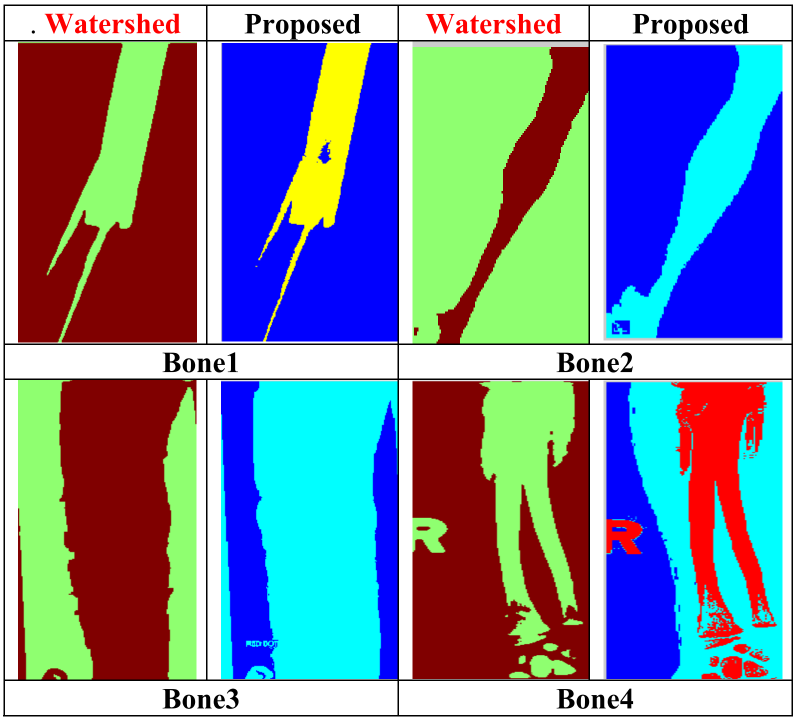


Figure 2 : Segmentation Result

For segmentation algorithm to be perfect, there should be clear distinction between the various regions of the image and the edges of these regions has to be identified unmistakably [4]. Supporting this theory, the proposed model segments the image in a more accurate fashion, by dividing it into more regions separating it using random colours. The edges of the image are more evident in the proposed model while the same cannot be held good for the base model, which clearly supports the argument that the segmentation process is more reliable and accurate in the proposed system.

4.2. Speed of Segmentation

Segmentation speed is the time taken by the algorithm to segment or divide the input image into regions. The time taken by the proposed and base algorithms is shown in Table 1. The graph (figure-3) shows the segmentation time of proposed and Base. The segmentation systems were developed using MATLAB 7.3 and were tested in a Pentium IV machine with 512 MB RAM.

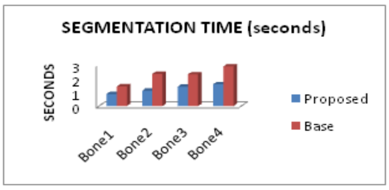
5. Conculsion

The algorithm runs exceedingly fast and can produce results in seconds. From the results projected, it is evident that the proposed method is an improved version to segment bone images. All these results stress the fact that the proposed method combining wavelets and morphological transform based segmentation algorithm has improved the existing system and can be used by other bone image analysis algorithms. In future, the effect of segmentation during fracture detection is analyzed.

Table 1 : Segmentation Time (Seconds)

Image	Proposed	Base
Bone1	.88	1.43
Bone2	1.12	2.34
Bone3	1.41	2.31
Bone4	1.59	2.89

Figure-3



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