Trabecular Bone Image Segmentation Using Iterative Watershed and Multi Resolution Analysis

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Abstract

Usually, bone fragility risk is related to deteriorations of osseous architecture. However, medical imaging is one of the means to appreciate in vivo bone screen, such as microscopic or micro-tomography images, which is important in the follow up of the osteoporosis. In this paper, a new image segmentation technique of trabecular bone images is introduced. It combines both hierarchical watershed segmentation, wavelet and image mosaic transform. The wavelet transform is applied to the intensity image, to de-noise the image, enhance edges in multiple resolutions, creating detail and approximation coefficients. Gradient magnitudes of the approximation image at the coarsest resolution are computed. The hierarchical watershed and the image mosaic transform are then applied to the approximation image at a given resolution. The segmented image is projected up to higher resolutions using the inverse wavelet transform. This technique provides robust segmentation results for images; reduces the watershed algorithm over-segmentation and results in closed homogeneous regions.

Keywords: *Trabecular bone, Hierarchical segmentation, Wavelet transform, Watershed transform, Image mosaic.*

1. Introduction

The equilibrium of bone remodeling can be affected by various diseases, the most frequent being osteoporosis [1], leading to a weakening in bone competence [2]. An ideal way to determine bone quality would be an in vivo or in vitro measurement able of detection and quantification of changes in bone microstructure [3]. Our task is to develop a way of determining whether a given pixel in a trabecular bone image contains pure marrow or is occupied by bone. For this reason, the image segmentation is a fundamental task in image analysis [4]. Therefore, segmentation method should provide a division of the image into separated regions, each one representing a different object. The watershed transform is a region-based image segmentation mathematical morphology algorithm; it can obtain the one-pixel width, uninterrupted and accurate boundary. Typically, the gradient magnitude of the original image is computed before the watershed transformation is applied. However, it leads to the over-segmentation problem because it is quite sensitive to the image noises [5]. Consequently, some new approaches were proposed to improve the watershed algorithm [6]-[7]-[8]-[9]. Such approaches are usually based on image transformations that change image resolution, in order to be able to segment objects of different sizes. Specially, small details are detected in higher resolution images, while larger items are segmented in coarser images. In fact, in this paper, a new morphological segmentation technique based on image mosaic transform, wavelets and watersheds is presented. The first step of this technique is to describe an image in multiple resolutions using stationary wavelet decomposition. A certain resolution 2J is chosen, and morphological gradient magnitudes at that resolution are estimated. Then the mosaic image transform is applied to remove spurious gradient and the hierarchical watershed is applied. This segmented image is projected to higher resolutions using the inverse stationary wavelet transform, until the full resolution.

This paper is arranged as follows, firstly, in section 1; we give a brief description of the watershed transform. Then, we present an overview of the multi-resolution analysis based on stationary wavelet transform. In section 2, we present the steps of the segmentation technique at the coarsest resolution using watersheds and the used alternative to shrink over-segmentation. In section 3 we describe the projection of the Segmented Image to Higher resolutions. Finally, we present experimental results in section 4. Conclusions are drawn in section 5.

2. The Watershed Representation and the Stationary Wavelet Transform

2.1. The Watershed Representation

The watershed algorithm comes from the field of grey scale mathematical morphology. This transformation is initially proposed by Digabel and Lantuejoul [10] and later enhanced by S. Beucher [11]. The watershed has been widely studied in several image segmentation problems. The gradient magnitude image to be segmented is considered as a topographic surface where the value of each pixel represents the altitude at that position. In consequence, the gradient image boundaries represent watersheds lines and low-gradient grey levels correspond to catchment basins. From the same minimum of a catchment all water converges towards. In consequence, the surface is slowly immersed, until filling all the catchment basins, starting from the basin that is related to the global minimum. If two catchment basins tend to join, a barrier is built. These barriers define the watersheds. The watershed algorithm divides the image into sets of connected pixels and allocates at every pixel a label of the local minima. The results present many inconvenient, such as over-segmentation, sensitivity to noise, and poor detection of important areas with low-contrast borders.

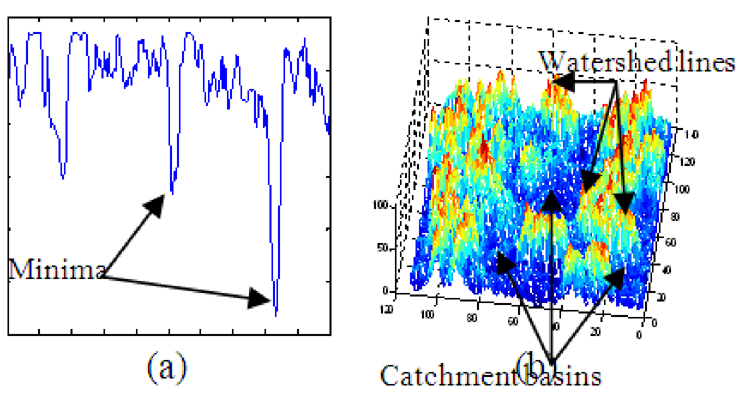


Figure 1. Trabecular bone profile image: (a) 2D and (b) 3D

The efficient watershed algorithm was developed by Vincent and Soille [12] who used an immersion-based approach and the most powerful implementation described in the literature uses hierarchical queue for the actual flooding. We present a brief review of this standard segmentation algorithm for the discrete case.

2.1.1. The Geodesic Skeleton by Zones of Influence (SKIZ): The simplest way to describe the geodesic skeleton by zone of influence transform [13] is by these operators listed as follows: Let x_i : connected components, X : a set composed of "n" connected components, K : Number of regions and "a" and "b" two points of "X". We call:

- The geodesic distance $d_X(a,b)$ $in\, X$ is the lower length of the path in "X" linking "a" and "b".
- The geodesic influence zone $iz_X(x_i)$ of a x_i in X is the set of the points of X for which the geodesic distance to x_i is smaller than the geodesic distance to other connected components of X as:

$$iz_{X(x_i)} = \{a \in X, \forall j \in [1,K]/\{i\}, d_X(a,x_i) \prec\} d_X(a,xj) \qquad \text{eq(1)}$$

- The skeleton by influence zone of x_i in X, denoted by $SKIZ(X(x_i))$, is the set of points of X which do not belong to any influence zone as shown in Fig2 :

$$SKIZ_X(x_i) = X / IZ_X(x_i)$$
$$where\ IZ_X(x_i) = \bigcup_{i\in[1,K]} iz_X(x_i). \qquad \text{eq(2)}$$

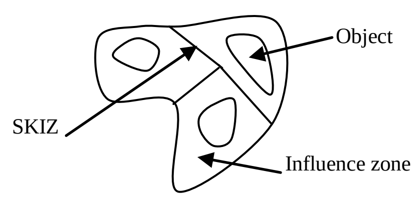


Figure 2. SKIZ Identification.

2.1.2. Watershed Algorithm: The principle of the watershed algorithm on the gray level by recurrence is; let "f" a bounded function. We note:

1) $h_{\min} = \min f \quad and \quad h_{\max} = \max f$

2) $[f]^h$ The upper threshold of "f " at level h :

3) Reg_minh (f) the set of the regional minima of "f" at level "h".

We calculate the geodesic influences zones of Xh+1 and, then we reiterate, such as:

i) $X_{h\min} = f_{h\min}$

ii) $X_{h+1} = \operatorname{Re}g\_\min_{h+1}(f) \cup IZ_{[f]^{h+1}}(X_h) \quad \forall h \in [h_{\min}, h_{\max} - 1]$

When the level "h = maxf" is reached, the process brings to an end and we have:

- The set of catchment basins of "f" is the set X_{hmax} obtained.
- The watershed of "f" is the complementary of X_{hmax}.

2.2. The Stationary Wavelet Transform

The discrete wavelet transform [14] is a mathematical tool that is successful in representing a signal both in time/spatial and frequency domains. The wavelet transform of a function, f, with respect to a specified mother wavelet "ψ" is defined as:

$$W_a f(x) = f * \Psi_a(x) = \frac{1}{a}\int_{-\infty}^{+\infty} f(t)\Psi\left(\frac{x-t}{a}\right)dt \qquad \text{eq(3)}$$

Where: "a" is the scale parameter (dilation). For all integers j≠0, setting a = 2j, then the wavelet transform is called dyadic DWT and it can be calculated as:

$$S_{2^j} f(n) = \sum_k h_k S_{2^{j-1}} f(n - 2^{j-1}k)$$
$$W_{2^j} f(n) = \sum_k g_k S_{2^{j-1}} f(n - 2^{j-1}k) \qquad \text{eq(4)}$$

Where $f(n)$: Digital signal, S_{2^j} : smoothing operator of digital signal $f(n)$ and $W_{2^j} f(n)$: Wavelet transform of digital signal $f(n)$.

In the following we consider: h_j : Coefficients of high-pass filters, g_j : Coefficients of low-pass, H : Orthogonal wavelet high-pass filter, G : Orthogonal wavelet low-pass filters, SWT : Stationary wavelet transforms and $ISWT$: Inverse stationary wavelet transforms.

According to Mallat's pyramid algorithm, the 2-D discrete wavelet transform computation involves recursive filtering and sub-sampling; and at each level, it decomposes a 2D signal into four sub-bands. Thus, the results of wavelet transform at each level are half the size of the original sequence. The SWT proposed by Nason and Silverman [15], is a wavelet transform algorithm. So, the difference is the SWT pads the corresponding low-pass and high-pass filters with zeros and the two new sequences which each have the same length as the original image [16]. The high-pass filter $H^{[r]}$ is obtained by introducing a zero between every adjacent pair of elements of the filter $H^{[r-1]}$, and similarly for $G^{[r]}$. This can be envisaged in the followed Fig3.

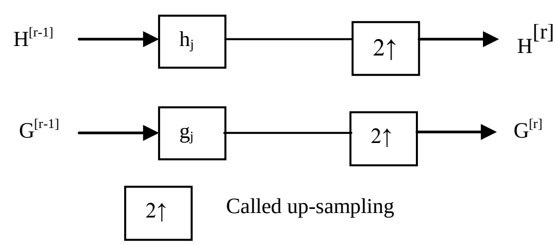


Figure 3. Up-sampling Process of Filter Coefficients

In summary, after applying the SWT method, the approximate image, at each level, is transformed into four pieces which can be denoted as LLj, LHj, HLj, HHj as in the graphic illustrated in Fig.4. The LLj sub-band is obtained from low pass filtering in both horizontal and vertical directions and it represent the original image and subsequently is called the approximated sub-band. The others pieces LHj, HLj and HHj are named detailed components. She represents the edge in horizontal, vertical and diagonal direction. The HHj component is the result of high pass filtering in both vertical and horizontal directions.

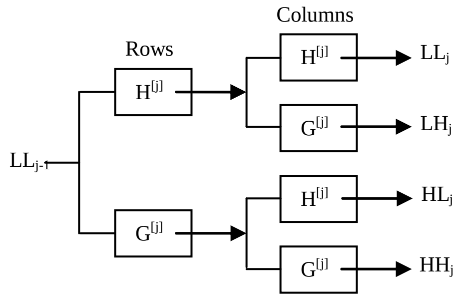


Figure 4. Decomposition Process of SWT

The main application of the SWT is de-noising. On the other hand, it gives a better approximation than the discrete wavelet transforms (DWT) seeing as, it is redundant, linear and shift invariant [17]. In this paper, we use the stationary wavelet transform to decompose trabecular bone image. For the reason that, the multi-resolution analysis enables us to decrease in the amount of noise and also remove the small details from image and only large objects will remain. For simplicity, we have used the Haar wavelet. Since, it is orthogonal and symmetric.

3. Watershed Segmentation at the Coarsest Resolution

The proposed algorithm can be summarized into the following steps presented in this schema block:

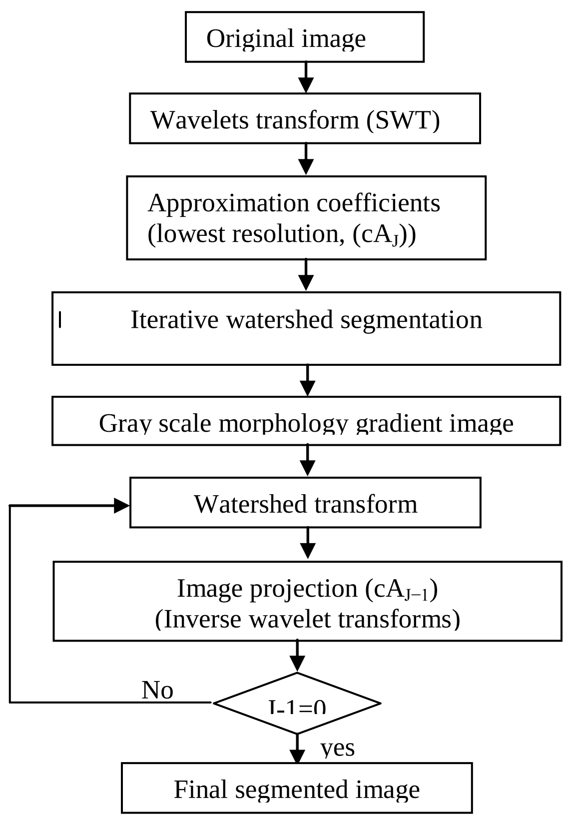


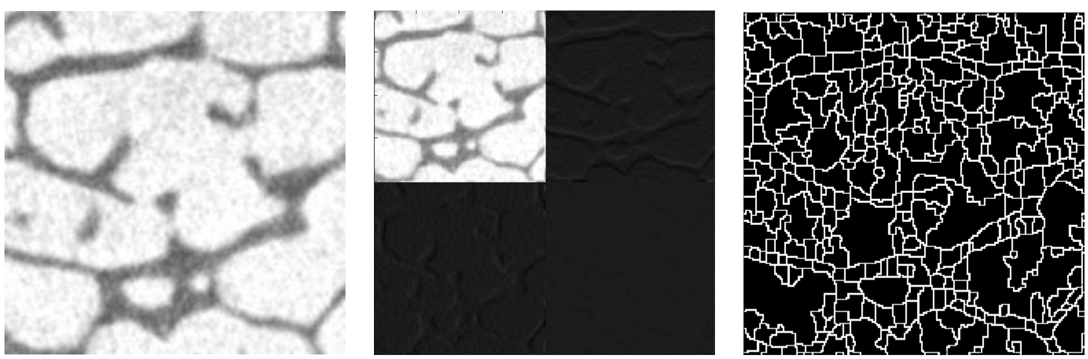
Figure 5. Flow Chart of Algorithm.

The first stage of the proposed segmentation method is to choose the initial resolution 2J, and compute the wavelet representation up to that resolution. The trabecular bone image is decomposed into different resolutions using stationary wavelet transform explained as above as shown in fig.4. Therefore, the processing is achieved on a low-resolution image, reducing the computation cost. Additionally, a great benefit in the use of the multi-resolution method is the possibility of reducing the over-segmentation of the watershed transformation and de-noising the image. After the decomposition process, the lowest-resolution approximation image A2J is segmented through the application of a watershed algorithm. The classical way of using the watershed algorithm to produce an object's contours is to work on the morphological gradient of the image. The morphological gradient is obtained as:

$$Grad(I) = D(I,B) - E(I,B) \qquad \text{eq(5)}$$

Where $Grad$: Gradient image, $D(I,B)$: Dilated image "I" by the structuring element B and $E(I,B)$: Eroded image "I" by the structuring element B.

In spite of noise was reduced when the approximation image "LL_2^J" at the lowest resolution was obtained (because of low-pass filtering), residual noise still exist, causing spurious gradients. So, the over-segmentation problem still exists and this initial segmentation generates multiple segmentation regions and separates the trabecular bone image into many small regions as illustrated in Fig.6. To prevent this over-segmentation and compute the more contrasted contours, an iterative segmentation is applied to the initial segmented image, based on the hierarchical watershed transform, imposing the selective minima on the gradient image and a simplified version of the original approximation image called mosaic image.



(a) (b) (c)

Figure 6. Initial Segmentation: (a) Original Image, (b) Lowest Resolution, (c) Initial Segmentation by Watershed.

3.1 Hierarchical-based Watershed Image Segmentation Algorithm

In this stage, we present the concept of hierarchical segmentation, developed by Beucher [14]-[15], and produced by the classical watershed transformation. The principle is to suppose that the highest contrast boundaries correspond to the object to be segmented. Through every step of the hierarchical segmentation, we try to remove the lowest contrast boundaries surrounded by higher values edges by merging the catchment basins of deleted edges. Such a process can be iterated to remove on a new pass, the becoming lowest edges. The simplest hierarchical segmentation algorithm is based on the reconstruction of the gradient mosaic image.

3.1.1. The Mosaic Image: The mosaic image [18] denoted also simplified image is computed by the following steps:

- Consider a grey tone image "I".
- Determine the corresponding morphological gradient: grad(I).
- Calculate the watershed of the gradient image: WT(grad(I)).
- Compute the average grey value of "I" inside each minimum of grad(I).
- Fill every catchment basin of the watershed with the average gray value of "I" corresponding to the minimum of grad(I).

This operation is detailed in [18]. The following figure shows the trabecular bone image mosaic and its morphological gradient.

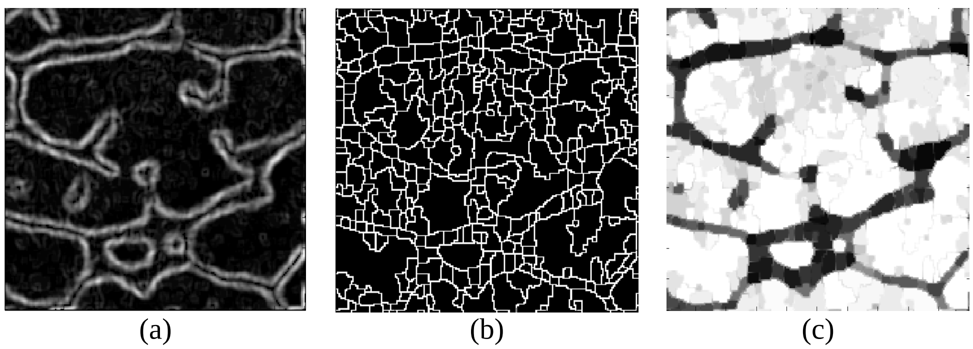


Figure 7. The Mosaic Image Transform: (a) Morphological Gradient Image, (b) Watershed Transform, (c) Image Mosaic.

3.1.2. Hierarchical Segmentation: The steps of building the hierarchical segmentation algorithm [19] called as the cascade algorithm are:

- Compute the image mosaic gradient: "grad_mosaic".
- Calculate the watershed of the gradient image: WT(grad_mosaic).
- Define a new image "A" as:

$$A(x) = \begin{cases} grad\_mosaic & si\ x \in WT(grad\_mosaic) \\ +\infty & si\ x \in WT^{C}(grad\_mosaic) \end{cases}$$

$$\text{Where that } A \geq grad\_mosaic \qquad \text{eq(6)}$$

With WT : Watershed lines and WT^{c} : Watershed lines complementary.

- Apply a geodesic reconstruction by erosion of "A" over "grad_mosaic":

$$[grad\_mosaic]^{recon} = \varepsilon^{recon}_{grad\_mosaic}(A)$$

In fact, geodesic reconstruction [20] fill each catchment basin with a height value plateau equal to the depth of the watershed line surrounding the corresponding catchment basin as shown in Fig8.

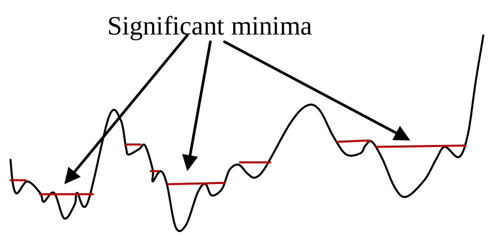


Figure 8. The Geodesic Reconstruction of the Signal

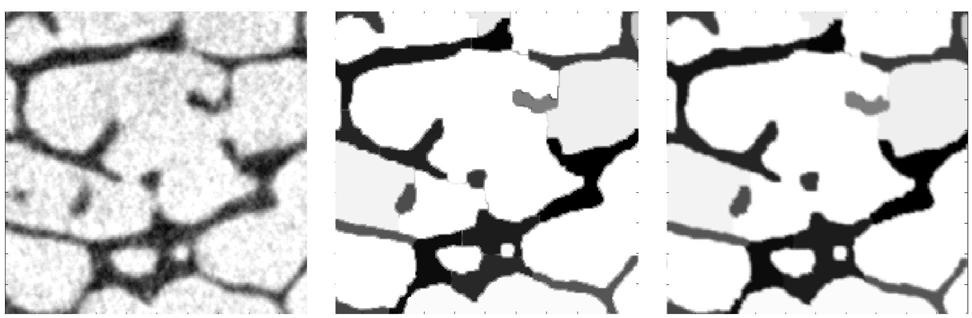
- Calculate the watershed of the image.
- From this last watershed, building a new mosaic image, after that calculates the morphological gradient to obtain: $[grad\_mosaic]_2$. Then we iterate the algorithm to obtain the hierarchy until the number of labeled regions is unchanged or a maximum number of iterations are reached. We have imposed the selective minima (regional minima of the image) on the gradient image. This is used as stopping criterion.

4. Projection of the Segmented Image to Higher Resolutions

After generating the segmented image at the resolution "J", each segmented region is designed with a label. The next step is the projection of the image by the Inverse Stationary Wavelet Transform $ISWT$ to obtain the full resolution image segmentation. Direct projection of the segmented image offers very poor results. Since the high frequencies (edges) is not taken into consideration in the segmentation process. In order to solve the overlapping problem, the major process of the projection to the full resolution is:

1) Compute the simplified image called "S_2^J" by applying the mosaic image transform to the segmented image.
2) Set the high frequency coefficients (LH_2^j, HL_2^j, LL_2^j, for j = 1, 2, … , j) as 0.
3) Wavelet reconstruction of "S_2^J" to obtain a higher resolution image S_2^{J-1}.
4) Applying to this last image the proposed iterative watershed segmentation presented in the previous section.
5) Application of the steps (1) and (2) to the last obtained image and projection by the inverse wavelet transform to the next level "S_2^{J-2}".
6) This process is repeated until the full resolution image is obtained.

The projection of the simplified image for the original trabecular bone images from resolution 2^3 to the full resolution are shown in Figure 9.



(a) (b) (c)

Figure 9. (a) The Original Image, (b) The Simplified Image S_2^3 of the Original Image at Resolution 2^3, (c) The Simplified Image S_2^0 of the Original Image at Full Resolution

5. Results and Discussions

In this section, the experimental results are illustrated to demonstrate the feasibility and validity of the proposed technique. We apply this strategy of segmentation to 30 different medical images acquired from the computerized micro-tomography with the size of 200x200 pixels and 8 bit/pixels resolution in order to accurately recognize the trabecular bone space from the medullar space. Figure 10 shows the segmentation result using watershed algorithm based on hierarchical segmentation.

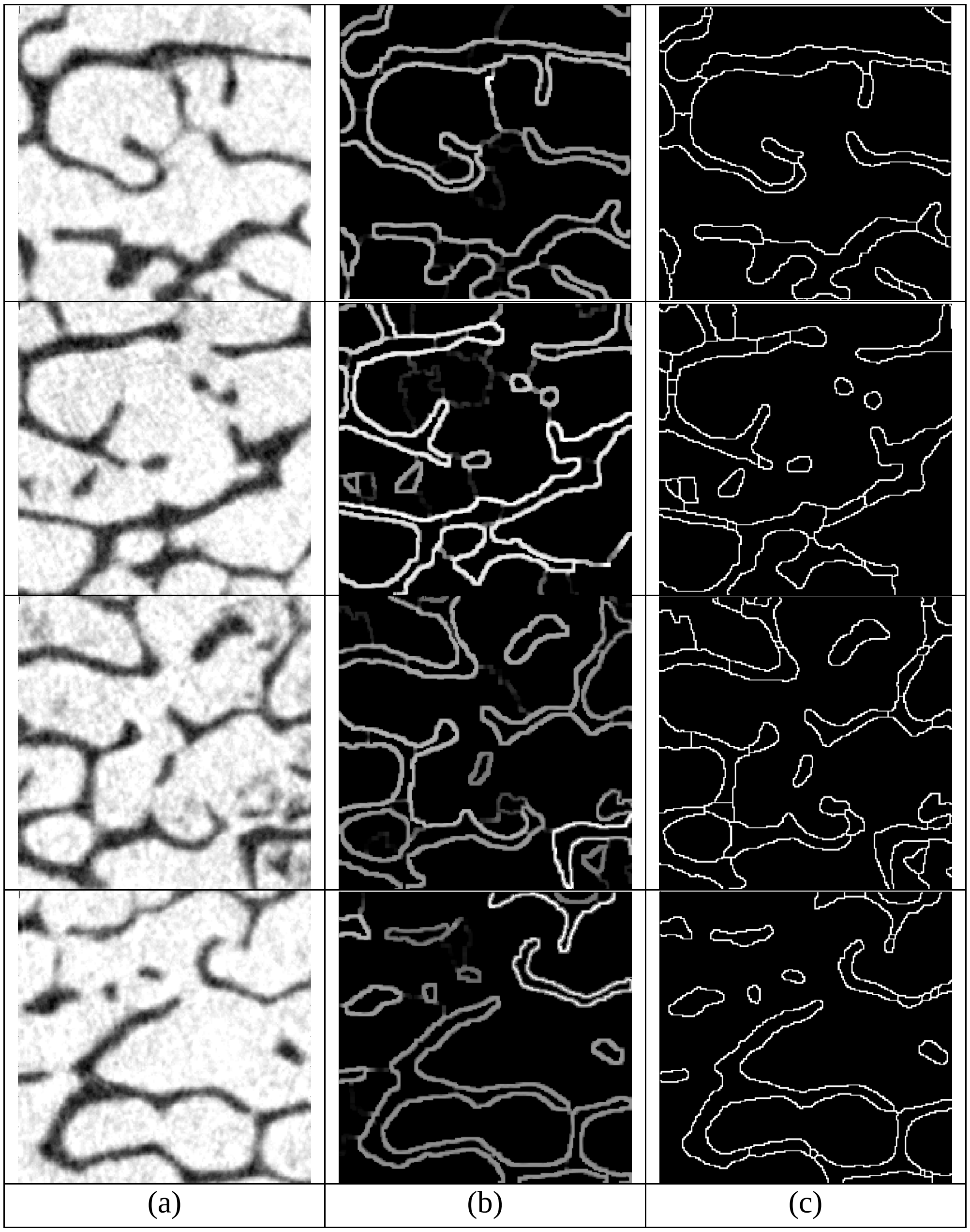


Figure10. (a) The Original Image, (b) The Morphological Gradient Image, (c) The Final Segmentation by the Proposed Process

The over-segmentation problem and the noise sensitiveness of the conventional watershed segmentation algorithm are overcome by the proposed segmentation algorithm. From the obtained results, we can see that the results are satisfactory, successfully segmenting the trabecular bone image, with nearly no over-segmentation existing.

6. Conclusion

In order to find good segmentation result, it is required to use the characteristics of the original image. According to the characteristics of trabecular bone images, a new strategy of segmentation is proposed. Firstly, the stationary wavelet transforms are used to remove the image noise. Also, the low-resolution image has less number of regions, shorter computational time. Finally, based on the characteristics of the sub-images, selective minima and image mosaic transform, a hierarchical watershed transform is applied. The experiment results show that the scheme can segment the trabecular bone images successfully and accurately. This proposed technique is used so as to help the doctors, to extract some parameters from the trabecular bone image in a short time.

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