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ScienceDirect
Magnetic Resonance Imaging 24 (2006) 1023–1029
MAGNETIC RESONANCE IMAGING

Characterization of trabecular bone structure from high-resolution magnetic resonance images using fuzzy logic

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Received 4 January 2006; accepted 7 April 2006

Abstract

The purpose of this work was to apply fuzzy logic image processing techniques to characterize the trabecular bone structure with high-resolution magnetic resonance images. Fifteen ex vivo high-resolution magnetic resonance images of specimens of human radii at 1.5 T and 12 in vivo high-resolution magnetic resonance images of the calcanei of peri- and postmenopausal women at 3 T were obtained. Soft segmentation using fuzzy clustering was applied to MR data to obtain fuzzy bone volume fraction maps, which were then analyzed with three-dimensional (3D) fuzzy geometrical parameters and measures of fuzziness. Geometrical parameters included fuzzy perimeter and fuzzy compactness, while measures of fuzziness included linear index of fuzziness, quadratic index of fuzziness, logarithmic fuzzy entropy, and exponential fuzzy entropy. Fuzzy parameters were validated at 1.5 T with 3D structural parameters computed from microcomputed tomography images, which allow the observation of true trabecular bone structure and with apparent MR structural indexes at 1.5 T and 3 T. The validation was statistically performed with the Pearson correlation coefficient as well as with the Bland-Altman method. Bone volume fraction correlation values (r) were up to .99 (P<.001) with good agreements based on Bland-Altman analysis showing that fuzzy clustering is a valid technique to quantify this parameter. Measures of fuzziness also showed consistent correlations to trabecular number parameters (r>.85; P<.001) and good agreements based on Bland-Altman analysis, suggesting that the level of fuzziness in high-resolution magnetic resonance images could be related to the trabecular bone structure.

Keywords: Trabecular bone; High-resolution magnetic resonance imaging; Fuzzy logic; Segmentation

1. Introduction

Osteoporosis is a metabolic disorder that manifests with changes in bone density and structure accompanied by the increased susceptibility to fractures [1]. Osteoporosis is commonly diagnosed and treated based on bone mineral density (BMD) studies; however, current research is focusing on assessing the potential of structural analysis to complement the characterization of bone in health and disease states to study and improve treatment effects. Although cortical bone also suffers the effects of osteoporosis, the researchers have focused on the trabecular bone because the turnover rate is considerably higher [1].

The feasibility and potential of assessment of trabecular bone quality with high-resolution magnetic resonance imaging (HR-MRI) has been demonstrated in different studies [1–7]. Image processing techniques based on microstructural parameters [2–6] and textural analysis [7] have been widely studied and validated to characterize trabecular bone with HR-MRI. However, few studies have taken into account the inherent fuzzy nature of these images due to the spatial resolution, which is in the order of the trabecular thickness causing substantial partial volume effects. The theory of fuzzy logic, first introduced by Zadeh [8], is well suited to the study of fuzzy images, and it has been used in image processing especially in the form of hard image segmentation with fuzzy c-means (FCM) clustering. Although the theory of topological fuzzy parameters for digital images was introduced in 1979 by Rosenfeld [9] and indexes of fuzziness and geometrical fuzzy parameters have been developed, these concepts have not been applied to the characterization of trabecular bone with HR-MRI, with the exception of Saha and Wehrli [10] who presented a study of the fuzzy distance transform (FDT) to measure trabecular bone thickness.

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doi:10.1016/j.mri.2006.04.010

The purpose of this work was to create a framework entirely based on fuzzy logic to the study of bone quality with HR-MRI. Ex vivo images of human radii at 1.5 T and in vivo images of human calcanei at 3 T were acquired, preprocessed with fuzzy logic techniques and segmented into to the categories of bone and marrow by using soft segmentation based on FCM. The fuzzy output (membership function) of this segmentation corresponding to the category of bone was taken as a fuzzy bone volume fraction (*f*-BVF) map. Three-dimensional (3D) geometrical parameters and measures of fuzziness were then computed from *f*-BVF maps and statistically compared to standard trabecular bone (Tb) microstructural indexes obtained from corresponding microcomputed tomography (μCT) images of human radii and to apparent (app.) Tb microstructural parameters obtained from corresponding MR images of human radii at 1.5 T and calcanei at 3 T. The objective of this comparison was to explore the possibility of finding trabecular bone structural information in the fuzzy parameters.

2. Background

2.1. Fuzzy logic

Zadeh [8], in his seminal work *Fuzzy Sets*, introduced the theory of fuzzy logic. Fuzzy sets are an extension of crisp sets. Crisp sets do not allow partial memberships; they only allow full or null membership of an element x to the set A, i.e.,

$$\mu_A(x) = 1 \text{ if } x \in A, \tag{1}$$

and

$$\mu_A(x) = 0 \text{ if } x \notin A, \tag{2}$$

where $\mu_A(x)$ represents the membership of x to A.

In fuzzy sets, partial memberships are allowed. The range of $\mu_A(x)$ is [0, 1] instead of {0, 1} as for crisp sets, and the set A is defined as

$$A = \{(x, \mu_A(x)) | x \in U\}, \tag{3}$$

where U is the universe of discourse.

2.2. Fuzzy c-means

Conventional clustering algorithms like K-means use crisp memberships for allocating samples to clusters. In a conventional clustering algorithm, the feature vectors are assigned to one and only one cluster or category [11]. However, in applications such as MRI, partial volume effects are present, and voxels could belong to different tissue categories with different levels of membership. Part of the volume of a voxel could belong to the category of bone, but another fraction could belong to the category of marrow. In these cases a clustering technique that allows partial memberships such as FCM could be used.

Given a set of n feature vectors $\mathbf{X}=(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n)$ in R^p, then FCM could be used to classify each feature vector $\mathbf{x}_j$ into c fuzzy subsets or clusters with different levels of membership μ_{ij}, which represents the membership of $\mathbf{x}_j$ to the ith cluster with the following conditions:

$$0 \le \mu_{ij} \le 1 \text{ for all } i \text{ and } j, \tag{4}$$

$$\sum_{i=1}^{c} \mu_{ij} = 1 \text{ for all } j \tag{5}$$

and

$$0 < \sum_{j=1}^{n} \mu ij < n \text{ for all } i. \tag{6}$$

FCM accomplishes these conditions iteratively by minimizing the following cost function:

$$J = \sum_{j=1}^{n} \sum_{i=1}^{c} \mu_{ij}{}^{m} ||x_j - v_i||^2, \tag{7}$$

where v_i is the ith fuzzy subset center and m is a heuristic constant greater than unity controlling the amount of fuzziness in memberships with a typical value of $m=2$. FCM converges to a solution for $\mathbf{v}_i$ that represents a local minimum or a saddle point of the cost function. In this iterative process, the membership functions as well as the cluster centers are updated.

2.3. Fuzzy geometrical parameters

Geometrical relationships between the image components play a key role in intermediate image processing [12]. Fuzzy perimeter and compactness were extended to 3D and investigated in this work as possible parameters to characterize trabecular bone structure. Considering a 3D region of interest (ROI) of size $I \times J \times K$ voxels, where the value of each voxel $\mu_{i,j,k}$ represents the level of membership to a specific category, the volume of the ROI was defined as

$$volume(ROI) = \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K} \mu_{i,j,k}, \tag{8}$$

and the perimeter as

$$\begin{aligned} Perimeter(ROI) = & \sum_{i=1}^{I-1} \sum_{j=1}^{J} \sum_{k=1}^{K} ||\mu_{i,j,k} - \mu_{i+1,j,k}|| \\ & + \sum_{i=1}^{I} \sum_{j=1}^{J-1} \sum_{k=1}^{K} ||\mu_{i,j,k} - \mu_{i,j+1,k}|| \\ & + \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{k=1}^{K-1} ||\mu_{i,j,k} - \mu_{i,j,k+1}||. \end{aligned} \tag{9}$$

Then, the 3D *compactness* was represented as

$$\text{compactness(ROI)} = \frac{\text{volume(ROI)}}{[\text{perimeter(ROI)}]^3} \tag{10}$$