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SOFT CLASSIFICATION OF TRABECULAE IN TRABECULAR BONE

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ABSTRACT

Classification of trabecular bone aims at discriminating different types of trabeculae. This paper proposes a method to perform a soft classification from binary 3D images. In a first step, the local structure tensor is used to estimate a membership degree of every voxel to three different classes, plate-, rod- and junction-like trabeculae. In a second step, the global structure tensor of plate-like trabeculae is compared with the local orientation of rod-like trabeculae in order to discriminate aligned from non-aligned rods. Results show that soft classification can be used for estimating independent parameters of trabecular bone for every different class, by using the classification as a weighting function.

Index Terms— Biomedical image analysis, trabecular bone, classification of tissue, structure tensor, micro computed tomography

1. INTRODUCTION

Osteoporosis is a medical condition in which the strength of bones is reduced leading to an increased risk of fracture [1]. Research in trabecular bone has been fostered by evidence supporting that osteoporosis mainly affects the trabecular bone and that its architecture largely determines the biomechanical properties of the bone.

Trabecular bone can be thought of as a network of interconnected “plate-like” and “rod-like” trabeculae whose architecture varies with the skeletal site [2]. Some studies have reported that plate- and rod-like trabeculae have different influences on mechanical properties of trabecular bone. In addition, the orientation of rods has been found important for assessing the mechanical competence of the bone [3, 4, 5]. This suggests that plates and rods aligned in different orientations may have different physiological purposes [5].

These studies require accurate classification algorithms for separating plates from rods. Most classification methods in the literature apply topological analysis techniques to a skeletonized version of the trabecular bone [5, 6, 7]. However, the “plate-rod” model should be seen as a simplification of the architecture of trabecular bone, since real trabecular bone is not composed by ideal plates and rods. Moreover, trabecular bone also contains junctions. Thus, these algorithms can bias the estimation of parameters such as trabecular thickness or fabric tensors. In addition, accuracy of skeleton-based classification methods largely depends on resolution [8].

Thus, rather than a hard classification, a soft classification scheme appears more appropriate for trabecular bone in which a degree of membership to each class is computed for every voxel. This is the approach followed in this paper. To the best of our knowledge, only [9] has followed this approach so far. They use the local inertia

tensor for every voxel to compute a function that ranges between -1, for ideal plates, and 1, for ideal rods. However, their approach fails in junctions and requires an adaptive estimation of the neighborhood at every voxel, which can involve high computational costs.

Thus, this paper proposes a method to estimate degrees of membership for every voxel to three different classes: plate-, rod-, and junction-like trabeculae by analyzing the local structure tensor. In addition, rods are also subclassified into aligned and non-aligned depending on their alignment with plate-like trabeculae. The computed degrees of membership can be used to independently estimate parameters, such as trabecular thickness or fabric tensors, for each class.

The paper is organized as follows. Section 2 presents the proposed segmentation method and shows how the new method can be used to estimate parameters of the bone for the different types of trabeculae. Section 3 shows and discusses the results of experiments conducted on synthetic datasets and images acquired through Micro Computed Tomography (μ CT). Finally, Section 4 makes some concluding remarks.

2. CLASSIFICATION METHOD

The classification problem can formally be stated as follows. Let C be a set of n classes, c_i be the i -th class, and $\mathbf{p}$ be a point in the trabecular bone. A classifier must estimate a membership function $m_{\mathbf{p}}(c_i) \in [0, 1]$ such that:

$$\sum_{i=1}^n m_{\mathbf{p}}(c_i) = 1. \quad (1)$$

The main difference between soft and hard classifiers is that the latter compute a binary membership function instead of a real valued one. That is, for hard classifiers, $m_{\mathbf{p}}(c_i)$ is exactly one for only a single class and zero for the other classes. In the following, classes plate-, rod- and junction-like are represented by c_1 , c_2 and c_3 respectively. In addition, subclasses aligned and non-aligned rods, which constitute c_2 , are represented by c_{2_1} and c_{2_2} respectively.

The proposed method consists of two steps. First, the local structure tensor (LST) is used to estimate $m_{\mathbf{p}}$ for classes c_1 , c_2 and c_3 . The estimated membership function is used to compute the global structure tensor (GST) of the plate-like trabeculae. In a second step, this tensor is used to estimate $m_{\mathbf{p}}$ for the subclasses c_{2_1} and c_{2_2} . These steps are explained in more detail below.

The LST aims at estimating local features in images. The LST can be computed as the convolution of a Gaussian with the outer product of the gradient with itself [10], that is:

$$S = G_{\sigma} * \nabla u \nabla u^T \quad (2)$$

Fig. 1. The initial estimation of $\mathbf{q}$ is compensated by applying simulated gravitational forces.

where S is the LST at all points of the trabecular bone, G_σ is the Gaussian with zero mean and standard deviation σ , ∇u is the gradient of the image u and $\nabla u \nabla u^T$ is the outer product of the gradient with itself at every point. The LST at a point $\mathbf{p}$, $S_{\mathbf{p}}$, is a symmetric semidefinite positive second order tensor that can be represented through an ellipsoid whose orientation and anisotropy are determined by its eigenvectors and eigenvalues respectively. $S_{\mathbf{p}}$ can be decomposed as:

$$S_{\mathbf{p}} = \sum_{i=1}^3 \lambda_i \mathbf{e}_i \mathbf{e}_i^T \quad (3)$$

where λ_i and $\mathbf{e}_i$ are its i -th largest eigenvalue and eigenvector respectively. Equivalently, $S_{\mathbf{p}}$ can be expressed as the sum of three tensors, namely $P_{\mathbf{p}}$, $R_{\mathbf{p}}$ and $J_{\mathbf{p}}$, which are given by:

$$P_{\mathbf{p}} = s_1 \mathbf{e}_1 \mathbf{e}_1^T, \quad (4)$$

$$R_{\mathbf{p}} = s_2 (\mathbf{e}_1 \mathbf{e}_1^T + \mathbf{e}_2 \mathbf{e}_2^T), \quad (5)$$

$$J_{\mathbf{p}} = s_3 (\mathbf{e}_1 \mathbf{e}_1^T + \mathbf{e}_2 \mathbf{e}_2^T + \mathbf{e}_3 \mathbf{e}_3^T), \quad (6)$$

where $s_1 = (\lambda_1 - \lambda_2)$, $s_2 = (\lambda_2 - \lambda_3)$, and $s_3 = \lambda_3$. $S_{\mathbf{p}}$ has three extreme cases. The first case occurs when $s_1 > 0$ and $s_2 = s_3 = 0$ and corresponds to a point in an ideal plate whose orientation is perpendicular to $\mathbf{e}_1$. The second case arises when $s_2 > 0$ and $s_1 = s_3 = 0$ and corresponds to a point in an ideal rod whose orientation is parallel to $\mathbf{e}_3$. Finally, the third extreme case results when $s_3 > 0$ and $s_1 = s_2 = 0$ and corresponds to a point in an ideal junction in which no orientation is preferred. In general, $S_{\mathbf{p}}$ can be seen as a linear combination of these three extreme cases.

The membership function $m_{\mathbf{p}}$ can be estimated as a function of s_1 , s_2 and s_3 . Let $\hat{s}_i = s_i / \lambda_1$, $\mathbf{c} = [c_1 \ c_2 \ c_3]^T$ and $\hat{\mathbf{s}} = [\hat{s}_1 \ \hat{s}_2 \ \hat{s}_3]^T$. Function $m_{\mathbf{p}}$ can be expressed as:

$$m_{\mathbf{p}}(\mathbf{c}) = f(\hat{\mathbf{s}}) \quad (7)$$

where f is a function that complies with (1). The simplest choice of f is the identity, that is, $m_{\mathbf{p}}(\mathbf{c}) = \hat{\mathbf{s}}$. However, this function requires the use of large values of σ for the Gaussian in (2), which is inconvenient since $S_{\mathbf{p}}$ could mistakenly be influenced by adjacent trabeculae. In general, σ must be chosen large enough to enable the computation of the LST at the center of the trabeculae but, at the same time, small enough to avoid inappropriate influence from adjacent trabeculae. A good trade-off is usually attained by setting σ to a half of the mean trabecular thickness. Under this conditions, the identity function leads to overestimations of $m_{\mathbf{p}}(c_1)$. However, this bias can be compensated by choosing a different function f . Let us consider the spatial locus of all possible $\hat{\mathbf{s}}$. As seen on Figure 1,

this space is a triangle whose corners $[1 \ 0 \ 0]$, $[0 \ 1 \ 0]$ and $[0 \ 0 \ 1]$ correspond to ideal plates, rods and junctions respectively. Notice that junctions correspond to intersections between plates and non-aligned rods, since intersections between plates can be seen as aligned rods. Thus, $\hat{\mathbf{s}}$ can be seen as the barycentric coordinates of a point $\mathbf{q}$ in such a triangle. The strategy is to use f to shift $\mathbf{q}$ to a more appropriate locus $\mathbf{q}'$ in the triangle. This shifting is given by:

$$f(\hat{\mathbf{s}}) = \hat{\mathbf{s}} + k_1 \mathbf{v}_1 + k_2 \mathbf{v}_2 + k_3 \mathbf{v}_3 \quad (8)$$

where $\mathbf{v}_i$ are the vectors that point the corners of the triangle from $\mathbf{q}$, and k_i are the barycentric coordinates of $\mathbf{q}'$. Factors k_i can be used to attract the point $\mathbf{q}$ to the corners, that is, to the extreme cases. One possibility is to compute k_i as simulated gravitational forces from $\mathbf{q}$ to artificial masses located at the corners. In that case, $k_i = h(\rho_i / \|\mathbf{v}_i\|^2)$ where ρ_i are masses located at the corners and h is a normalization constant.

Different attraction forces to the corners can be simulated by using different masses. The overestimation of plateness can be compensated by choosing $\rho_2 > \rho_1$. In addition, $\rho_3 \ll \rho_1$ in order to discourage junctionness. Values of $\rho_1 = 1$, $\rho_2 = 4$ and $\rho_3 = 0.25$ have yielded good results in the experiments of Section 3 for the aforementioned setting of σ .

After having classified trabecular bone into classes c_1 , c_2 and c_3 , the next step is to compute a membership function for the subclasses c_{21} and c_{22} . This classification requires the estimation of the main orientation of plate-like trabeculae in order to compare it with the orientation of rods. A standard method for estimating orientation is the Mean Intercept Length (MIL) tensor. However, the GST has also been found appropriate for such an estimation [11]. The GST for c_i , GST_i , can be computed through the membership function estimated in the first step as:

$$GST_i = \int_{\Omega} m_{\mathbf{p}}(c_i) S_{\mathbf{p}} d\Omega \quad (9)$$

where Ω represents the points in the trabecular bone.

The membership function for c_{21} and c_{22} can be estimated by comparing GST_1 with the third eigenvector, $\mathbf{e}_3$, of $S_{\mathbf{p}}$ at rod-like trabeculae. Thus, $m_{\mathbf{p}}(c_{21})$ can be estimated as:

$$m_{\mathbf{p}}(c_{21}) = m_{\mathbf{p}}(c_2) \left(1 - \frac{\langle GST_1, \mathbf{e}_3 \mathbf{e}_3^T \rangle^2}{\|GST_1\|_F^2} \right) \quad (10)$$

where $\langle A, B \rangle = \text{trace}(AB^T)$ is the inner product of matrices and $\|\cdot\|_F$ is the Frobenius norm, which is applied to normalize the result. Since the two subclasses are complementary, $m_{\mathbf{p}}(c_{22}) = m_{\mathbf{p}}(c_2) - m_{\mathbf{p}}(c_{21})$. This formulation take advantage of the fact that inner product increases with the alignment between GST_1 and the orientation (given by $\mathbf{e}_3$) of the rod.

The membership function can be used as a weighting factor to compute different parameters of trabecular bone. For example, bone volume and surface estimations for different classes, BV_i and BS_i , can be computed as:

$$BV_i = \int_{\Omega} m_{\mathbf{p}}(c_i) d\Omega \quad (11)$$

$$BS_i = \int_{\Gamma} m_{\mathbf{p}}(c_i) d\Gamma \quad (12)$$

with Γ being the interface between bone and marrow. In the experiments, these parameters are given as percentages of bone volume (BV) and bone surface (BS) respectively.

Fig. 2. Soft classification results for the synthetic models. Levels of red, green and blue have been used to mark plate, and aligned and non-aligned rods respectively. Junctions only occur inside the bone.

In turn, thickness for different classes, $Tb_i.Th$, can also be estimated by using m_p . For example, [12] computes thickness as twice the mean of the Euclidean distance, d , at the medial axis of the bone, Λ . Thus, $Tb_i.Th$ can be estimated by using the membership function as a weighting function at Λ as:

$$Tb_i.Th = 2 \frac{\int_{\Lambda} m_p(c_i) d_p d\Lambda}{\int_{\Lambda} m_p(c_i) d\Lambda} \quad (13)$$

with d_p being the Euclidean distance at p . In addition, the MIL tensor can also be computed for every class as follows. The MIL requires the computation of intercepts between the interface between bone and marrow and a set of parallel lines [13]. Thus, a MIL tensor for every class can be obtained by weighting every intercept by m_p at that point.

3. RESULTS AND DISCUSSION

Experiments have been conducted on synthetic models and images acquired through μ CT. Figure 2 shows the classification results for two synthetic models. The first one includes two plates ($BV_1/BV = 73\%$, $BS_1/BS = 73.5\%$, $Tb_1.Th = 4$), four aligned ($BV_2/BV = 10.6\%$, $BS_2/BS = 12.8\%$, $Tb_2.Th = 7$) and four non-aligned rods ($BV_3/BV = 16.4\%$, $BS_3/BS = 13.7\%$, $Tb_3.Th = 9$), and eight junctions (between the non-aligned rods and the plates). These plates and rods are assumed to be sections of plates and rods of infinite length. As seen on Fig. 2a, the proposed method correctly classifies the different types of trabeculae. It is important to remark that $m_p(c_{21})$ increases close to the junctions. This result was expected since non-aligned rods also contain a small component of plateness that generates aligned rods in the intersections with the plates.

The second model shows a transition between an aligned rod and a plate with a constant thickness of nine. Figure 2b shows that the method appropriately computes the smooth transition from class c_{21} to class c_1 . In addition, it can be seen that the edges of the plate have a strong component of aligned rodness. This is because an edge is equivalent to an intersection between two plates, which are modeled by the method as an aligned rod. Considering edges not to be an integral part of plates is advantageous, since the core of a plate could have different mechanical properties from those of its edges. Furthermore, since edges of plates in trabecular bone are rounded, they can be seen as rods juxtaposed to plates. Thus, plateness should be reduced at edges, whereas rodness should be increased. Moreover, the top of the rod has also a component of plateness (the color at its center is a mixture between blue and red). This result was also expected since the top of the rod is actually a small plate.

Fig. 3. Top: rendering of volumes of interest of a vertebra (left) and a radius (right). Some non-aligned rods are marked in red. Bottom: soft classification results for the vertebra (left) and the radius (right) using the color conventions of Fig. 2. The images have an isotropic resolution of $82\mu m$ and $20\mu m$ for the vertebra and radius respectively.

Figure 3 shows a rendering and the soft classification of two μ CT images. These images correspond to volumes of interest of a vertebra and a radius respectively¹. In both cases the eigenvector corresponding to the smallest eigenvalue of GST_1 was parallel to the z axis. This means that, for these images, plate-like trabeculae are mainly oriented vertically. It can also be seen that the vertebra and radius have a different composition since the former contains many rods, both aligned (vertical) and non-aligned (horizontal) with the plates, while the latter has more plates and fewer rods.

Table 1 shows volume, surface, thickness and anisotropy measurements independently computed for each class on the datasets of Fig. 2 and 3. The degree of anisotropy of the GST_i tensor, $GST_i.DA$, which is given by the ratio between the maximum and minimum eigenvalues of GST_i , has been used as an estimation of anisotropy. These parameters have been computed both for soft and hard classification in order to assess differences between them. The hard classification for classes c_1 , c_2 and c_3 , $m'_p(c_i)$, has been obtained as:

$$m'_p(c_i) = \begin{cases} 1, & \text{if } i = \operatorname{argmax}_i m_p(c_i) \\ 0, & \text{otherwise.} \end{cases} \quad (14)$$

In addition, the hard subclassification of rods has been generated by applying a similar strategy for subclasses c_{21} and c_{22} on points where $m'_p(c_2) = 1$.

As seen on the table, parameters computed with soft and hard classification for the synthetic models are close to the ground-truth, with errors below 3% for BV_i and BS_i and below 1 voxel for $Tb_i.Th$. In addition, anisotropy measurements are in agreement with the expected values. Thus, either soft or hard classification can be used in datasets with ideal plates and rods. It should be noticed that $GST_3.DA$ of soft classification can have values greater than one,

¹We thank Prof. Osman Ratib from the Service of Nuclear Medicine of the Geneva University Hospitals for providing the μ CT data of the vertebra and Andres Laib and Torkel Brismar for providing the μ CT data of the radius.

Table 1. Parameters estimated for each class for the synthetic models of Fig. 2 (s_a and s_b), vertebra (v) and radius (r) datasets, by applying soft and hard classification. Subindex t refers to parameters computed on the entire image.

	BV _i /BV [%]					BS _i /BS [%]					Tb _i .Th [mm]					GST _i .DA						
	c ₁	c ₂	(c ₂₁)	(c ₂₂)	c ₃	c ₁	c ₂	(c ₂₁)	(c ₂₂)	c ₃	t	c ₁	c ₂	(c ₂₁)	(c ₂₂)	c ₃	t	c ₁	c ₂	(c ₂₁)	(c ₂₂)	c ₃
s _a - Soft	73.5	25.9	(12.7	13.3)	0.6	76.2	23.4	(12.1	11.3)	0.4	6.62	4.22	7.15	(6.30	8.25)	7.39	6.22	52.29	1.38	(2.05	22.39)	5.52
s _a - Hard	71.8	28.0	(13.0	15.0)	0.2	73.9	26.1	(13.8	12.3)	0.0	6.62	4.01	6.67	(6.33	8.25)	8.25	6.22	127.31	1.51	(1.93	18.50)	1.06
s _b - Soft	68.5	30.7	(30.4	0.3)	0.8	65.6	33.3	(32.7	0.6)	1.1	9.00	9.00	9.00	(9.00	9.00)	9.00	5.88	19.69	2.30	(2.32	1.02)	5.31
s _b - Hard	66.8	33.1	(32.8	0.3)	0.1	63.4	36.6	(35.8	0.8)	0.0	9.00	9.00	9.00	(9.00	9.00)	9.00	5.88	35.46	2.15	(2.17	1.49)	1.03
v - Soft	49.3	46.8	(34.4	12.4)	3.9	46.2	49.5	(35.7	13.8)	4.3	0.31	0.32	0.30	(0.30	0.28)	0.28	1.52	2.00	1.43	(1.55	1.18)	1.42
v - Hard	49.4	50.5	(49.4	1.1)	0.1	44.2	55.7	(54.4	1.4)	0.1	0.31	0.33	0.29	(0.29	0.26)	0.21	1.52	2.22	1.30	(1.33	2.22)	1.03
r - Soft	55.8	41.4	(32.3	9.1)	2.8	56.2	41.1	(32.0	9.1)	2.7	0.20	0.19	0.20	(0.20	0.20)	0.20	1.85	2.14	1.72	(1.81	1.48)	1.82
r - Hard	59.7	40.3	(40.3	0.0)	0.0	60.3	39.7	(39.7	0.0)	0.0	0.20	0.19	0.20	(0.20	-)	0.18	1.85	2.21	1.61	(1.61	-)	1.05

since GST₃.DA must be interpreted as the anisotropy at the neighborhoods of ideal junctions. For example, in the first synthetic dataset, points at these neighborhoods are mainly oriented with the plates, leading to the reported increase of anisotropy.

However, hard classification is not suitable for the μ CT images. In particular, the estimation of volume and surface for class c_{2_2} is largely affected by hard classification. Although non-aligned rods are clearly visible in Fig. 3 (some of them have been marked in the rendered volumes), hard classification ignores them, biasing the estimations of parameters. An extreme case appears in the radius dataset, where no voxel was hard classified as non-aligned rod. That means that more elaborate hard classifiers are necessary for the tested μ CT images, where ideal plates and rods are not longer present. However, this step is not necessary to estimate parameters for different classes, since these can appropriately be estimated from a soft classification.

Moreover, it is interesting to remark that results for μ CT images are in accordance with previous works, since parameters computed for every class can be very different from those computed on the entire image. In addition, it should be noticed that $BV_{2_1} \gg BV_{2_2}$ in μ CT images. This result can be related to the bone remodeling process, since part of plates can be resorbed, generating aligned rods.

4. CONCLUDING REMARKS

This paper has proposed a method to perform a soft classification of trabecular bone based on the LST and GST. The classification has been used for estimating independent parameters of trabecular bone for every different class, by using the degree of membership as a weighting function.

Results have shown that the proposed method appropriately discriminates among the different types of trabeculae. Thus that the hard classification process, which may introduce errors and whose results can always be questioned, can be circumvented by using our soft classification approach.

Plans for future research include finding correlations between parameters computed with the proposed soft classifier and mechanical properties of the bone. This will allow us to assess their potential for characterizing trabecular bone.

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