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A Comparison of Wavelet, Curvelet and Contourlet based Texture Classification Algorithms for Characterization of Bone Quality in Dental CT

T. Kalpalatha Reddy[1*], Dr. N. Kumaravel[2]

[*1.] SKR Engineering College/ ECE, Anna University, Chennai, India,Email:rddylth@gmail.com

[2]. College of Engineering / ECE, Anna University, Chennai, India.

Abstract: The objective of this paper is to design and implement classifier framework to assist the surgeon for preoperative assessment of bone quality from Dental Computed Tomography images. This article focuses on comparing the discriminating power of several multiresolution texture analysis methods to evaluate the quality of the bone based on the texture variations of the images obtained from the implant site using wavelet, curvelet and contourlet.The approach consists of three steps: automatic extraction of the most discriminative texture features from regions of interest, creation of a classifier that automatically grades the bone depends on the quality. Since this is medical domain, the validation against the human experts is carried out. The results indicate that the combination of the statistical and multiscale representation of the bone image gives adequate information to classify the different bone groups compared to gray level features at single scale.

Keywords: Multiresolution analysis, texture classification, Wavelets, Ridgelets, Curvelets, Contourlets, Dental Computed Tomography.

1. Introduction

Implant dentistry is the treatment of choice to replace missing teeth in both partially and completely edentulous patients (Shearer 1995). Pre-operative evaluation of bone density is essential to assist the clinician with the treatment planning of implant therapy. Bone classification by Lekholm and Zarb (1985) using the radiographic image and tactile sensation when cutting the bone (Freiberg 1995) is commonly used to determine the bone quality in dental implantology (Fig 1).

At present, clinically available dental CT does not provide sufficient resolution to resolve trabecular structures. Therefore, instead of measuring structural parameters directly there is a trend to use textural or statistical descriptors to characterize the trabecular architecture without requiring stringent segmentation of the individual trabeculae.Thus the methods described in this paper will allow estimates of structural parameters from CT images, providing for the first time, the possibility of clinical use of such estimates.

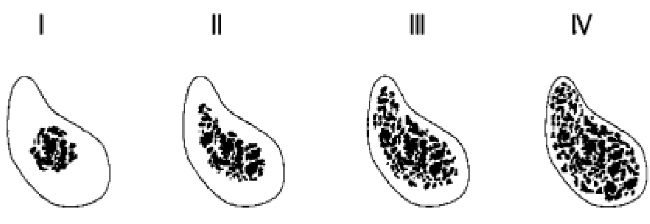


Figure 1 Classification of Bone Quality according to Lekholm and Zarb (1985)

Co-occurrence matrices are often used in texture analysis since they are able to capture the spatial dependence of gray level values within an image. Run length matrices are able to capture the coarseness of texture in specified directions as defined by gray level runs. The process of segmenting the ROI from CT images through manual and semi automatic process considers pixel gray level values and does not consider the spatial distribution of pixels in image. Hence the research focuses on multi-resolution analysis of multi wavelet taken in to account the impact of spatial distribution of pixels and the threshold transacting through the transformation coefficients at different resolution levels. Inspired by the success of wavelets, a number of new multiresolution analysis tools like contourlet, ridgelet and curvelets etc have been developed to resolve directional features. The traditional multiresolution methods keep an eye on the spectral information of the texture image at different scales and use the statistics of the spectral information as the texture descriptor but they ignore the texture structural information.

To make use of the texture primitives, histogram and GLCM are combined with the traditional multiresolution method so that a better classification of bone quality becomes possible. The appropriate multi-resolution transform was applied and a set of texture descriptors were extracted from the transformed image. These features characterized the textural properties of the images and were used to train the classifier to recognize each texture class.

2. Methodology

The texture classification algorithm consists of three main steps: segmentation of regions of interest, extraction of the most discriminative texture features, creation of a classifier that automatically identifies the various bone groups and correlating significant texture parameters with insertion torque.

2.1. The data set

Sixty five patients referred for single or multiple tooth implant treatment at the incisor, canine or premolar regions of the maxilla or the mandible are enrolled in this study. All surgery was undertaken by one surgeon who also evaluated the bone quality according to the classification described by Lekholm and Zarb (1985). The images were acquired with multi slice spiral CT scans (120 kV and 300mAs, with a slice thickness of 0.625mm, pitch 0.4mm, scan time 750msi GE medical systems). The 3D DICOM image data consists of 190 consecutive 2D slices, each slice being 512x512 pixels in size and having 16 bit gray level resolution. Each slice is therefore further cropped to the respective sizes because of size requirements of 2^n for wavelets and a prime size for ridgelets. Fig.2, Fig.3 and Fig.4 shows an example of dental CT scan and a processed and cropped slice of the bone.

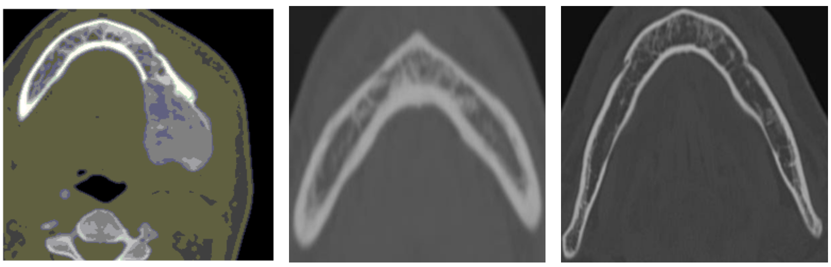
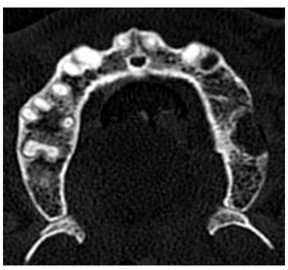


Figure 2 Axial View of Maxilla and Mandible CT images



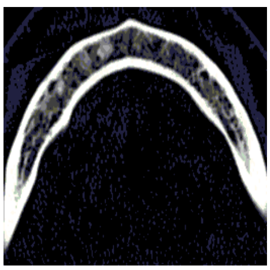


Figure 3 Enhanced Bone Images (Background Removed)

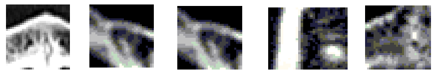


Figure 4 Recipient Implant Sites (ROI)

2.2. Feature extraction

Once the medical images were pre-processed as described in section 3.1, the following multiresolution transforms were applied and textural feature vectors were then extracted: Gabor wavelet, Coiflet wavelet, ridgelet, curvelet and contourlet .After the transforms were applied, first and second order statistics were extracted for use in classification. The classification step was carried out using a decision tree classifier based on C&RT approach, Support Vector Machine, Adaboost and Bayes classifier. The classification performance of the classifier is then estimated by constructing a confusion matrix. A confusion matrix is a table that lists bone groups and its true positives, true negatives, false positives and false negatives

3. Results

Table 1 illustrates a comparison of accuracy results for bone quality for the best wavelet based (Coiflet), best curvelet based (energy) and best contourlet based (pooled) feature sets. The contourlet based descriptors clearly outperforms all wavelet, ridgelet and curvelet-based descriptors. The wavelet scale co-occurrence features had significantly higher performance measures in comparison to Gabor and ridgelet based descriptors, with accuracy rates 1-13 % higher than any other wavelet based feature set under the classification rule of C&RT. Curvelet based descriptors had an even higher performance in comparison to both the wavelet families and ridgelet, with accuracy rates approximately 6-12% higher under the classification rule of SVM. Contourlet based features yielded accuracy rates between 90% and 97.69%, which significantly improved accuracy ranges for wavelet, ridgelet and curvelet based features. This was also expected since the bone textures exhibit more diverse directional components (curves or irregular shapes) which are well retrieved by the contourlets.

The contourlet based algorithm was also compared to three other non-wavelet based texture classification algorithms, co-occurrence, run-length and histogram. Although wavelet, ridgelet and curvelet based features performed lower than co-occurrence, the contourlet based features had a higher discriminative power than gray level texture features under the classification rule of C&RT and Adaboost as shown in Table 2. The contourlet algorithm had accuracy rates in the 88-97.7% range, compared to co-occurrence based algorithm with 92.1-93.1%, run length based algorithm with 71-90% and histogram based algorithm with 66-91.3% accuracy. The improved performance of the proposed contourlet directional energy feature sets providing the highest classification accuracy rates for a wide variety of classifiers. The combination of the statistical and multi-scale representation of the bone image gives adequate information to classify the different bone groups compared to gray level features at single scale. Thus it can be concluded that the contourlet based multiresolution texture analysis improves the performance of the radiographic methods.

Table 1 Comparison of the best wavelet, ridgelet, curvelet and contourlet based descriptors

Feature Set	**Classification accuracy (%)**				
	C&RT	**Adaboost**	**SVM**	**Bayes Classifier**	**LVQ**
Contourlet energy features	90.63	88	90	87.5	56.16
Contourlet pooled features	97.69	97.6	94	88.12	53.45
Gabor Energy	94	64	88.1	88.3	53.7
Wavelet Scale co-occurrence	95	80.3	89	80.75	67.9
Curvelet features	90.77	89.9	94	85.13	53.45
Ridgelet features	81.7	72.7	82	78.6	50

Table 2 Comparison of the contourlet, co-occurrence, run-length and histogram based descriptors.

Classifier type	Histogram / Run length /Co-occurrence/ Contourlet Classification Accuracy (%)	Time taken (min)*
C&RT	91.3 / 90 / 93.1/97.7	8
Bayes classifier	66.1 / 71.2 / 92.4/88	12
Boosting algorithm	91.1 / 88 / 92.4/97.6	20
SVM	83.4 / 88.3 / 92.1/94	5
Learning vector Quantization	66.43 / 64.78 / 78/55	10
*Algorithm run on MATLAB R2008b in Pentium 2GHz computer		

4. Summary

The research presented in this article is aimed to gain insight into some of the structural properties of trabecular bone and implement texture analysis methods for the assessment of trabecular architecture and quality from non- invasive low dose Dental CT images. The surgeons will know about the bone quality present in the jaw only at the time of explorative drilling in fixture site preparation.Hencs this system is designed to provide timely expertise regarding the loading, implant type and bone augmentation procedures based on the texture variations observed at the implant recipient sites. The knowledge required for the diagnosis is acquired from the implantalogists based on insertion torque (CRA). Insertion Torque gives an objective assessment of bone density but it does not give any information on bone quality until the osteotomy site is prepared.

This research focuses mainly on :(1). A multiresolution based feature extraction stage which maps an image sample onto a feature vector, so that each sample is represented by a point in an n-dimensional feature space, and (2) finding a decision rule to determine the class of a sample given its feature vector. It offers a comprehensive analysis of texture classification algorithms using five sets of wavelet, Gabor, ridgelet, curvelet and contourlet based texture features, as well as a comparison with three standard texture classification algorithms based on co-occurrence, run-length and histogram based texture features.

Methods were described to extract texture features from bone CT images by employing wavelet first order, second order and scale dependent statistics. Also the problem of rotation invariance and directional information has been studied by introducing non separable transforms. The quality of the proposed feature sets was illustrated on classification problems in characterizing and grading images of the jaw bone. Tests comparing the wavelet, ridgelet, curvelet and contourlet texture features indicated that contourlet based directional feature set outperform all other multiresolution techniques yielding accuracy rates in the 94-97.7% range. In comparison a similar algorithm based on wavelet yielded accuracy rates in the 80-95% range at best, the algorithm based on ridgelet texture descriptors yielded accuracy rates in the 73-82% range at best, and the algorithm based on curvelet texture descriptors yielded accuracy rates in the 85-94% range.

The paper also compares these multi-resolution techniques with standard co-occurrence, run-length and histogram based texture classification algorithms. Tests indicate that the contourlet based algorithm outperformed by 1-2% in accuracy rates for all the bone grades. The conclusion of the study is that evaluation of the coarseness of trabeculation of the alveolar bone texture as seen on computed tomographic images is a helpful clinical indicator of skeletal BMD and while dense trabeculation is a strong indicator of high BMD, sparse trabeculation may be used to predict low BMD.

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