

Designing a Feature Vector for Statistical Texture Analysis of Mandibular Bone

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Abstract

Objectives: This paper develops an algorithm to generate automatically, a feature vector using various statistical texture features of trabecular mandible from digital Orthopantomogram (OPG). These statistical features are computed using Gray Level Co-occurrence Matrices (GLCM) of mandible structure. **Analysis:** For this paper, region of interest is trabecular mandible bone present in lower jaw. Mandible Segmented from OPG is taken as input to the algorithm. GLCM of this mandible is calculated at four angles viz., 0°, 45°, 90° and 135° and for two gray scale intensities viz., 128 and 256. Various texture features are calculated from each of these GLCMs. These statistical features are compared and analyzed. **Findings:** 100 digital OPGs are used for analysis of statistical texture features. Four texture features contrast, viz., correlation, energy, homogeneity are calculated for the four angles mentioned above. **Improvement:** Texture analysis is performed on various types of images since last 50 years. Locating systemic disease features (e.g., Osteoporosis) from OPG is an upcoming research area. In this area, it is observed that comparatively less literature is available which uses GLCM texture features. The algorithm proposed here devices a texture feature vector for mandible. Analysis of the features is also presented in this paper.

Keywords: Digital OPG, GLCM, Mandible, Texture Analysis

1. Introduction

An Orthopantomogram (OPG) also known as „orthopantomogram“ or „panorex“, is a panoramic dental X-ray of the upper jaw (maxilla) and lower jaw (mandible)¹. OPGs are used by dental surgeons to get information regarding diagnosis and treatment of impacted wisdom teeth, periodontal bone loss, assessment of the placement of dental implants, orthodontic assessment, etc². Automatic classification of jaw bone cyst is successful on OPG images³. According to reference⁴, signs showing sensitivity to systemic diseases like osteoporosis, maxillary sinus abnormality and carotid artery calcifications are observed on OPG images. In references¹⁻⁶ Region of Interest (ROI) is mandible. Thus, correct segmentation and generation of feature vector for mandible are significant tasks to be addressed.

In³⁻⁶ image processing techniques are applied to separate ROI from OPG images e.g., cysts, fractures, osteoporoses, etc. In³, cyst regions are classified using basic statistical measures like average brightness, Standard Deviation (SD) and shape properties like oblong and circular. In⁵ uses active shape model which is a statistical point distribution model for detecting osteoporosis from OPG. In⁶ uses statistical measures viz., mean and SD of mandible width to detect low bone mineral densities in women. In⁷ uses mean, SD and regression method to establish association between carotid artery calcification and peripheral arterial disease, detected from OPG. Various statistical measures like mean, mode and variance have been calculated for classification of ROIs. The features used by above mentioned researchers address restricted localized problems and are very much application specific. Obviously, a need is felt to design a feature

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vector addressing all the application areas discussed above.

Texture is one of the important attributes to separate objects or regions. Literature available on statistical texture features includes explanation of theory and application of statistical texture features in specific areas¹⁻⁶. In⁸ presented theory of texture features using GLCM matrix. Paper focuses on four statistical features viz., angular second moment, contrast, homogeneity and correlation, using GLCM. Images used are photomicrograph data set, areal photographic images and satellite images. In⁹ present new texture feature 'trace' for applications related to content based image retrieval. Trace finds continuous region in the image by calculating summation of diagonal elements of GLCM. In¹⁰ differentiates normal brain and abnormal brain using GLCM statistical features from brain images. In¹¹ uses four GLCM features to classify retinal images as normal or infected. According to¹², for microtextures, statistical approaches seem to work well. These statistical approaches include auto-correlation functions, optical transforms, digital transforms, textural edgeness, structural element, gray tone co-occurrence and autoregressive models. As explained above⁹⁻¹¹ use GLCM to get features from various medical images.

Above discussion indicates that no much literature is available giving analysis of statistical features on OPG images. Thus, extensive analysis of OPG images is required to be addressed.

OPG images give indications about jaw illnesses and also get findings related to systemic diseases. Thus, structural features like width of trabecular mandible bone, lower and upper edges of mandible and mandible trabecular structure are important for the purpose of diagnosis. These structural features need to be analyzed for specific applications using statistical first order features like mean, mode, variance and second order GLCM features. Further, these structural and statistical features need to be considered to design a mandible feature vector. This feature vector can then further be used by intelligent classifier. This paper focuses on analysis of four statistical texture feature using GLCM for trabecular mandible bone.

GLCM describes the spatial association of the gray intensities in a textural pattern giving probability of gray-level i present at neighborhood of gray-level j at a distance d and direction. GLCMs can be calculated from an image using different values of d and and these probability values create the co-occurrence matrix $G(i, j | d, \theta)$ ¹³. The present paper considers four measures obtained from

GLCM for digital OPG images as input. They are contrast, correlation, homogeneity, and energy.

2. Methodology

For the proposed algorithm input image (.jpg) is a digital OPG. The algorithm includes various modules like, to segment mandible, to obtain GLCM, to obtain various statistical measurements and to obtain feature vector. Block diagram shows pictorial view of the proposed algorithm in Figure 1. Coding is done in MatLab R2013a.

2.1 Blockdiagram

2.2 Proposed Algorithm

Digital OPG mage is segmented to separate mandible automatically using strip method¹⁴ by dividing input image in five vertical strips viz., $St_1, St_2 \dots St_5$. Strip St_2 is considered as an input to the proposed algorithm to obtain texture features of mandible. Figure 2 shows image of sample input OPG and strip St_2 of the mandible.

2.3 Obtain GLCM

Gray Level Co-Occurrence Matrix is obtained for various angles like $0^\circ, 45^\circ, 90^\circ$ and 135° . For each of these angles, gray levels considered have intensity resolution as 256 and 128. Four texture measures considered are contrast, correlation, energy, homogeneity⁸.

2.4 Obtain Statistical Texture Features

Four features obtained for 100 digital OPG images are contrast, correlation, energy and homogeneity. In

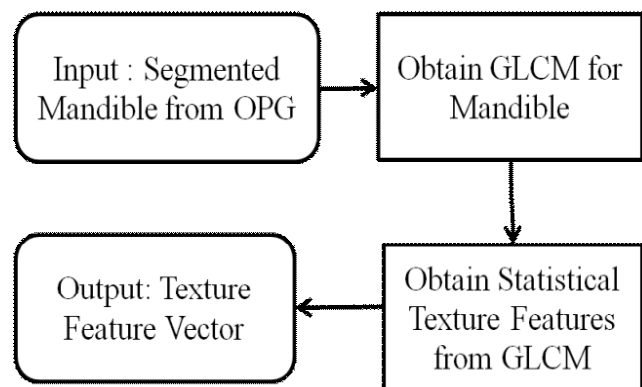


Figure 1. Block diagram of the proposed algorithm.



Figure 2. Digital OPG and segmented St_2 mandible.

an image, contrast measures local intensity changes. Contrast has zero value if image contains uniform intensities. Contrast has high value if intensity variation is large. Correlation, ranging from -1 to 1, measures how pixels are correlated to their neighboring pixels. For example, as compared to other angles, correlation count for vertical texture at 90° is high. Homogeneity measures the similarity of pixels. High homogeneity count indicates more pixels with similar intensity, i.e., textures have minimum intensity changes. Energy, also known as Angular Second Moment (ASM) gives uniformity in the image. Constant intensity image will have energy as 1.

3. Results

The developed algorithm is tested on 100 colored .jpg digital OPG images obtained from practicing dental professionals. For majority of the images, image size in pixel is 2440×1292 . Pixel resolution is 235 dpi with 24 bit depth. Table 1 shows averages of various texture features obtained from St_2 and St_4 strips. First Column indicates number of gray levels as 256 or 128 and angles as 0° , 45° , 90° , 135° for generating GLCM.

Four GLCM measures mentioned above are calculated using developed algorithm and are analyzed. Contrast measure indicates that intensity variations are present in mandible structure. Average contrast is observed to be as high as 571 for angle 45° for St_2 . For St_4 , it is as high as 578 for angle 135° . At 0° , values are minimal for contrast. This indicates that contrast is comparatively constant at 0° . From Figure 2, it can be observed that mandible structure is at some angles at St_2 and St_4 .

Correlation displays highest value at 0° . This indicates that, in mandible, horizontal texture property is prominent. As, at 0° , homogeneity count is high, it supports correlation. This means, similar intensity pixels are present in horizontal direction. Energy measure is

Table 1. Average of various texture features

Intensity, angle in degree	offset		St_2 Average				St_4 Average			
			Contrast	Correlation	Energy	Homogeneity	Contrast	Correlation	Energy	Homogeneity
256, 0°	0	1	230	0.96	0.018	0.77	229.6	0.96	0.019	0.77
256, 45°	-1	1	571	0.9	0.011	0.56	370.7	0.93	0.014	0.62
256, 90°	-1	0	379	0.93	0.014	0.67	381.7	0.93	0.015	0.67
256, 135°	-1	-1	374	0.93	0.012	0.62	578	0.9	0.012	0.57
128, 0°	0	1	57.2	0.96	0.018	0.8	57.1	0.96	0.019	0.8
128, 45°	-1	1	142	0.9	0.011	0.61	92.2	0.93	0.014	0.67
128, 90°	-1	0	94.4	0.93	0.014	0.71	94.99	0.93	0.015	0.71
128, 135°	-1	-1	93.1	0.93	0.012	0.67	143.8	0.9	0.012	0.62

also high in horizontal direction. Value of energy at 0° is highest as compared to other angles. When intensity count is reduced from 256 to 128, average contrast reduces. But other properties display almost same values. This indicates that values of correlation, energy and homogeneity do not change even if intensity count is reduced.

4. Conclusions

The algorithm proposed in this paper designs feature vector for trabecular mandible bone from lower jaw using statistical texture features. Algorithm works well for 100 digital OPG images and gives consistent results. It can be concluded from the values obtained that, these measures can be considered as attributes for feature vector. This paper has focused on statistical texture features of mandible using GLCM matrix. Algorithm determines four statistical measures viz., contrast, correlation, energy and homogeneity with two intensities as 128 and 256 and four angles 0° , 45° , 90° , 135° . Contrast feature gives evidence of angular structure in selected strips St_2 and St_4 . Correlation, energy and homogeneity texture features consistently show that horizontal texture in the mandible is strong. This horizontal texture needs to be processed further using image processing technique to get structural features. Statistical and structural features together, need to be analyzed. This feature vector will be useful in future to find traces of systemic disease like osteoporosis from digital OPG images.

5. References

1. Naik A, Tikhe S, Bhide DS, Kaliyamurthie KP, Saravanan T. Algorithm to detect fracture from OPG images using texture analysis. 6th IEEE International Advance Computing Conference, IACC; 2016. p. 374–85.
2. OPG Digital. Available from: <http://www.phmedicalcentre.com/opg.asp>
3. Mikulka J, Kabrda M, Gescheidtova E, Peina VC. Classification of jawbone cysts via orthopantomogram processing. 35th International Conference on Telecommunications and Signal Processing (TSP); 2012 Jul. p. 499–502.
4. Hayashi T, Matsumoto T, Sawagashira S, Tagami M, Katsumata AK, Hayashi Y, Muramatsu C, Zhou X. A new screening pathway for identifying asymptomatic patients using dental panoramic radiographs. Medical Imaging Computer-Aided Diagnosis. In van Ginneken B, Novak CL, editors. Proceedings of the SPIE. 2012; 8315:111–21.
5. Allen PD, Graham J, Farnell DJJ, Marjanovic EJ, Adams J, Jacobs R, Karayianni K, Lindh C, Stelt PFVD, Horner K, Devlin H. Detecting osteoporosis from dental radiographs using active shape models. IEEE International Symposium on Biomedical Imaging; 2007. p. 1256–9.
6. Amal RS, Mohammed M, Fatin Kh, Abbas A, Nuhad Al, Hassan H. Diagnostic efficacy of mandibular cortical thickness on panoramic radiographs to identify postmenopausal women with low bone mineral densities (Iraqi Population). Journal of American Science. 2013; 308–12.
7. Lee JS, Kim OS, Chung HJ, Kim YJ, Kweon SS, Lee YH, Shin MH, Yoon SJ. The prevalence and correlation of carotid artery calcification on panoramic radiographs and peripheral arterial disease in a population from the Republic of Korea: The Dong-gu study. Dentomaxillofacial Radiology the British Institute of Radiology. 2013; 42(1). 2972–5099.
8. Robert M, Haralick K, Shanmugam S, Dentein D. Texture features for Image classification. IEEE Transaction on Systems, Man and cybernetics. 1973; 3(6):610–21.
9. Sebastian B, Unnikrishnan A, Balakrishnan K. Grey level co-occurrence matrices: Generalisation and some new features. IJCSEIT. 2012; 2(2):151–7.
10. Kumaar MA, Thanaraj P. Feature extraction of arterio-venous malformation images using grey level co-occurrence matrix. Indian Journal of Science and Technology. 2015 Dec; 8(35):1–5.
11. Reshma CP, Chand J. Dheeba D. Automatic detection of color fundus retinopathy. Indian Journal of Science and Technology. 2015; 8(26):1–12.
12. Robert M, Haralick H. Statistical and structural approaches to texture. Proceedings of IEEE. 1979; 67(5):786–808.
13. Albregtsen F. Statistical texture measures computed from gray level cooccurrence matrices. Image Processing Laboratory Department of Informatics University of Oslo; 2018. p. 1–14.
14. Naik A, Tikhe S, Bhide S, Kaliyamurthie KP, Saravanan T. Indian Journal of Science and Technology. 2016; 9(21):1–6.