Analysis of Periapical Lesion Using Statistical Textural Features

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Abstract

In this work we present a quantitative study on different regions of periapical images with a series of textural features, extracted using cooccurrence matrices; those features are used for a pattern recognition analysis by means of an artificial neural network. The obtained results show that it is possible to recognize in an objective way changes in bone pattern.

1 Introduction

Radiographs are the most accurate diagnostic aid for the detection of osseous abnormalities in the maxilla and the mandible [1]. Density and gray-scale variations are important visual features the clinicians use to evaluate changes in bone pattern; yet the diagnostic accuracy of radiography for periapical bone lesion is limited, due to its dependency from the observer. Computerized analysis to help the decision-making process might be of significant value for improving the diagnostic process.

In this paper we present a quantitative study on different regions of periapical images with a series of textural features, extracted using co-occurrence matrices, to be used for a pattern recognition analysis; the classification step has been performed by means of an artificial neural network. The obtained results show that it is possible to automatically select different changes in bone patterns.

The paper is organized as follows: Section 2 presents a short review about the co-occurrence matrices method. In Section 3 some experimental results are presented; finally Section 4 drawns the conclusions.

2 Theoretical Background

Statistical techniques for texture analysis are based on the assumption that the relevant information in a texture image I is contained in the spatial relationship within the gray levels in the image. The Co-occurrence Matrix (CM) method has been proposed by Haralick in 1973 [2], and since then has been widely used for texture analysis; results reported in [3], [4] shows the effectiveness of this methods for the classification of periapical bone lesion texture.

The CM of an image I is defined as the matrix of relative frequencies P_{ij} with which two neighboring pixels, divided by distance d, occurr on the image, one with gray-level i and the other with gray-level j:

$$CM\Phi(d,\theta) = [P_{ij}(d,\theta)] \tag{1}$$

The CM is a function of the angular relationship between the neighboring pixels as well as a function of the distance between them. Typical choosed values for the angle θ are $0^0, 45^0, 90^0, 135^0$. For an N_g gray levels image, the CM will be of size $N_g \times N_g$. If N_g is too large, the number of pixel pairs contributing to each element of the CM will be low, and the statistical significance poor. On the other hand, if the number of gray level is too low, much of the texture information may be lost in the image quantization. It must then be stressed that the value of d is critical too for the analysis and it must be compared with the typical size of the texture pattern element; if d is too large, we are averaging over several texture elements, and we get random correlations; if d is too small, we are looking at details of the pattern.

In texture classification, individual elements of CMs are seldom used; instead, features are computed from the matrices. A large number of textural features have been proposed, starting with the original fourteen features described in [2]. According with the results reported in [4], we've used the set of features listed above:

$$f_1 = \sum_{i,j} \hat{f}(i,j)^2 \tag{2}$$

$$f_2 = -\sum_{i,j} \hat{f}(i,j) log(\hat{f}(i,j)) \tag{3}$$

$$f_3 = \sum_{i,j} \frac{(i-\mu_i)(j-\mu_j)\hat{f}(i,j)}{\sigma_i \sigma_j} \tag{4}$$

$$f_4 = \sum_{i,j} (i-j)^2 \hat{f}(i,j) \tag{5}$$

$$f_5 = \frac{\sum_{i,j}(ij)\hat{f}(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y} \tag{6}$$

where μ_x, μ_y, σ_x and σ_y are the means and standard deviations of row and column sums, respectively, and

$$\mu_i = \sum_i i \sum_j \hat{f}(i,j)$$

$$\mu_j = \sum_j j \sum_i \hat{f}(i,j)$$

$$\sigma_i = \sum_i (i-\mu_i)^2 \sum_j \hat{f}(i,j)$$

$$\sigma_j = \sum_j (j-\mu_j)^2 \sum_i \hat{f}(i,j)$$

3 Experimental Results

54 X-ray images, produced using an RVG system [1], were selected from the database of the School of Dentistry of the University of Rome 'La Sapienza' based on visual criteria and clinical results. From every image were selected two Region Of Interest (ROI), corresponding to regions where the periapical lesions were visible or not. The dimensions of ROIs varies from 10×10 pixels to 20×20 pixels; we've obtained a final database of 108 ROI.

Figure 1: An example of periapical lesion

	set1	set2
TP rate	0.89	0.91
FP rate	0.11	0.09

Table 1: Obtained results for the two different cases sets

We computed for every ROI the CMs and the five features as described in Section 2, with $N_g = 16$ gray levels, and $d = 1$; the results reported in [3] shows that for $d \geq 2$ there are no significant improvements.

A three-layers, feedforward, backpropagation neural network (with one neuron in the hidden layer) was learnt to classify the two different kinds of texture. Two different combinations of learning and testing sets were used, the sets being of 30 (set1) and 50 (set2) learning case, and 78 and 58 testing cases, respectively. In order to remove the dependency of a specific partitioning on the analysis, we decided to use 10 different partitions of the data set for setting up the learning and test sets. To evaluate the performance of the network, we considered the True Positive (TP) and False Positive (FP) rates of classification, where the TP rate is defined as the ratio of cases correctly classified to the total number of cases in the test set, and the FP rate as the ratio of cases misclassified to the total number of cases in the test set. The obtained results are shown in Table 1.

4 Conclusions

In this paper we presented a model, based on statistical textural features, able to classify different regions, in radiographic images of periapical lesions, in which the abnormalities are visible or not. The obtained results show the efficacy and robustness of this representation and, at the same time, encourage the development of this approach in order to obtain a follow-up system for supporting the decision-making process by physicians.

References

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