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Statistical Texture Analysis in Dental Panoramic Images for Cyst and Tumor Classification Using Support Vector Machine

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***Abstract*— Texture is one of the important characteristics used in identifying objects or region of interest in an image. The other side, many lesions (cyst and tumor lesions) that occur in the jaw have a similar radiographical appearance and it is often difficult to differentiate among them. Thus, we propose to use first-order statistics texture feature extraction to classify these lesions. Six features were extracted and using Support Vector Machine (SVM) based classification, the result showed that 6 texture features could differentiate cyst and tumor lesion with accuracy up to 84.62 %. Further analysis showed that Area Under the Receiver Operating Characteristic Curve (AUC) was 0.9361. This means that the prediction accuracy could be classified as very good.**

***Index Terms*— Cyst and tumor lesion, dental panoramic images, first-order statistics texture, Support Vector Machines**

I. INTRODUCTION

The human jawbone is a site of a variety of disorders. Various type of cyst and tumor lesions have been clinically classified [1–6].

In particular, there exist lesions (e.g. malignant tumor lesion) that have a potential to develop into cancer. Detection of malignant tumor in its early stages considerably reduces morbidity and mortality. Early detection also saves hundreds of millions that otherwise would be spent on the treatment of advanced-diseases. In clinical practice the decision about further treatment of the patient is predominantly based on lesion appearance from the visual part of dental panoramic images. Therefore by knowing the features of lesions and extracting the different features, the classification can be immediately performed and evaluated [7],[8]. A previous study evaluated the classification of lesions based on features with the lesions being manually segmented by medical experts [9]. However, this is still a challenging problem for computer vision due to the variability of the shape and appearance of cyst and tumor lesions. On the other hand, the machine is usually more efficient, after supervised learning, than humans in differentiation of oral diseases.

Currently our image database includes cases of two types of lesions, the cyst lesions and the tumor lesions. Both of the lesions typically have a smooth, round or oval periphery [4],[6] and are not easily differentiated, see Fig. 1. This situation makes the dentist unable to determine exactly whether it is a tumor or a cyst.

Research to differentiate tumor and cyst has never been conducted yet. Up to now, the furthest research conducted only talk about application to Oral Lesion Detection in Color Images Using Active Contour Models [9]. Thus, we conducted a research to distinguish between cyst and tumor lesion using Support Vector Machines (SVMs) based on texture features. Research based on texture has been done in [10–13], but the object of research are not in the field of dental panoramic image and classifier is not using SVM. We have used Gray Level Co-occurrence Matrix (GLCM) texture features to differentiate the cyst and tumor lesion [8], but the accuracy value is only 63.33%.

Thus, in this paper we propose an automatic assessment

(a)

(b)

Fig. 1. The cyst and tumor lesion on dental panoramic images. (a) cyst lesion (arrow), (b) tumor lesion (arrow).

using of first-order statistics texture, to extract the features of cyst and tumor lesions and classify these lesions using SVM. To evaluate the performance of SVM, we compute Area Under Receiver Operating Characteristic (ROC) Curve (AUC).

This paper is organized as follows : In section 2 we give the materials and methods concerning the first-order statistics texture, SVM, ROC and AUC. In section 3, we show the experimental result about the feature extraction and classification. After that, compute AUC from ROC curve to measure SVMs classifier performance Section 4, discusses the result and section 5 contains the conclusions.

II. MATERIALS AND METHODS

A. Materials

A dataset of 133 dental panoramic images including various of cyst lesion (radicular cyst, dentigerous cyst, buccal bifurcation cyst, keratocyst, calcifying odontogenic cyst, nasopalatine cyst, simple bone cyst) and various of tumor lesion (ameloblastoma, ameloblastic fibroma, adenomatoid odontogenic tumor, odontoma, cementoblastoma, torus palatinus, torus mandibularis, exostosis, enostosis, myxoma, osteoma, hemangioma, osteoid osteoma, osteo blastoma) derived from Oral Radiology [4] and Cranex 2.5^+ Soredex dental panoramic x-Ray Machine model PT-12SA, which the images already in digital form. The total cyst lesion is 53 images and total tumor lesion is 80 images. The position of the cyst and tumor regions were provided by an experienced radiologist.

B. Methods

In this paper, we develop method to classify cyst or tumor lesion using the properties of dental panoramic images. The steps of our method are as follow :

1. Preprocessing : a color image is first transformed into gray image by normalizing the values of its pixels with respect to the length of the gray scale . Using Gaussian filter to smooth the images. The region of interest (ROI) for each lesion was manually outlined by a well-trained operator and further confirmed by an experienced radiologist. The ROI of size 40 x 40 pixels is extracted with mass centered in the window, and divided into two sets : the learning set and the testing set.
2. Feature Extraction : using first-order statistics texture to extract the features of cyst and tumor lesions. We used a set of 6 statistics features. The 6 selected features are: mean, standard deviation, smoothness, third moment, uniformity and entropy.
3. Classification : using SVM method to classify the result of features from cyst and tumor lesion.
4. Evaluation : using AUC to evaluate the performance of SVM.

C. The first-order statistics texture

A frequently used approach for texture analysis is based on statistical properties of the intensity histogram [10]. The features from first-order statistics are mean, standard deviation, smoothness, third moment, uniformity and entropy. Where z_i is a random variable indicating intensity, *p(z)* is the histogram of the intensity levels in a region, *L* is the number of possible intensity levels, we compute the features using eq. (1-6).

Mean is a measure of average intensity :

$$m = \sum_{i=0}^{L-1} z_i \; p(z_i) \tag{1}$$

Standard deviation is a measure of average contrast :

$$\sigma = \sqrt{\sum_{i=0}^{L-1} (z_i - m)^2 \; p(z_i)} \tag{2}$$

Smoothness measures the relative smoothness of the intensity in a region :

$$R = 1 - \frac{1}{1+\sigma^2} \tag{3}$$

Third moment measures the skewness of a histogram :

$$\mu_3 = \sum_{i=0}^{L-1} (z_i - m)^3 p(z_i) \tag{4}$$

Uniformity, this measure is maximum when all gray levels are equal (maximally uniform) and decreases from there :

$$U = \sum_{i=0}^{L-1} p^2(z_i) \tag{5}$$

Entropy is a measure of randomness :

$$e = -\sum_{i=0}^{L-1} p(z_i) \log_2 p(z_i) \tag{6}$$

D. Classification

After the features have been extracted and selected, they are input into classifier to categorize the images into cyst or tumor lesion. We use Support Vector Machine (SVM) method to categorize these lesions.

D.1. Support Vector Machine (SVM) Classifier

SVM is a state-of-the-art classification method introduced in 1992 by Boser, Guyon & Vapnik [14] for binary classification. The key concept of SVMs, which were originally first developed for binary classification problems, is the use of hyperplanes to define decision boundaries separating between data points of different classes. SVMs are able to handle both simple, linear, classification tasks, as well as more complex, i.e. nonlinear, classification problems. Both separable and nonseparable problems are handled by SVMs in the linear and nonlinear case. The idea behind SVMs is to map the original data points from the input space to a high dimensional, or even infinite-dimensional, feature space such that the classification problem becomes simpler in the feature space.

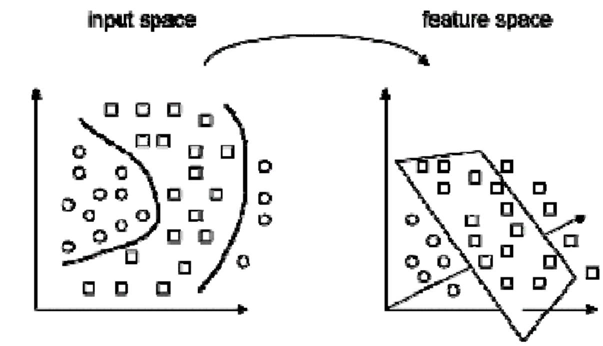

Fig. 2. SVMs allow mapping of the data from the input space to a high-dimensional feature space [15].

The mapping is done by a suitable choice of a kernel function. Kernel functions are used to map the input data into a higher dimension space then an optimal separating hyperplane in the high-dimensional feature space is chosen [7]. Consider a training data set $\{x_i, y_i\}$, with $x_i \in \Re^d$ being the input vectors and $y_i \in \{-1,+1\}$ the class labels. SVMs map the d-dimensional input vector x from the input space to the d1-dimensional feature space using a (non)linear function $\phi(.)$: $\Re^d \rightarrow \Re^{d1}$. The separating hyperplane in the feature space is then defined as $W^T \phi(x) + b = 0$, with $b \in \Re$ and W an unknown vector with the same dimension as $\phi(x)$. A data point x is assigned to the first class if $f(x) = \text{sign}(W^T \phi(x) + b)$ equals +1 or to the second class if $f(x)$ equals -1.

However, in our study, data of both classes are overlapping, which makes a perfect linear separation impossible. Therefore, a restricted number of misclassification should be tolerated around the margin. The resulting optimization problem for SVMs, where the violation of the constraints is penalized, is written as

$$\min_{W,b,\xi} \frac{1}{2} W^T W + C \sum_{i=1}^{N} \xi_i$$
$$\text{subject to} \quad y_i (W^T \phi(x_i) + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad i = 1, \ldots, N, \tag{7}$$

where C is a positive regularization constant. The regularization constant in the cost function defines the trade-off between a large margin and misclassifation error.

For non-separable data, the soft-margin SVM uses the slack variable (ξ) to control an upper bound of the misclassification error. The value of ξ_i indicates the distance of x_i with respect to the decision boundary. Equivalently, the optimization problem for SVMs can be written in the dual space using the Lagrangian with Lagrange multipliers $\alpha_i \geq 0$ for the first set of constraints [15]. The solution for the Lagrange multipliers is obtained by solving a quadratic programming problem. Finally, the SVM classifier takes the form :

$$f(x) = sign\left(\sum_{i=1}^{\#SV} \alpha_i y_i K(x, x_i) + b\right) \tag{8}$$

where #SV represents the number of support vectors and the kernel function K(.,.) is positive definite.

Furthermore, $K(x,x_i) \equiv \phi(x)^T \phi(x)$ is called the kernel function. In the optimization problem only K(.,.) is used which is related to $\phi(.)$. This enables SVMs to work in a high-dimensional (or infinite-dimensional) feature space, without actually performing calculations in this space. We use Gaussian Kernel in this study with kernel function is :

$$K(x, x_i) = \exp\left(-\frac{\|x - x_i\|^2}{2\gamma}\right) \tag{9}$$

where γ is the kernel parameter.

E. Evaluation

A receiver operating characteristic (ROC) curve is most frequently used because of its comprehensive and fair evaluation ability [7]. A ROC curve is a plotting of true positive fraction (TPF) as a function of false positive fraction (FPF) [16], [17]. The area under the ROC curve (AUC) can be used as a criterion. Table I shows the classifying level of accuracy based on AUC [16].

Other frequently used criteria are [18] :

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{10}$$

$$specificity = \frac{TN}{TN + FP} \tag{11}$$

$$sensitivity = \frac{TP}{TP + FN} \tag{12}$$

where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives and FN is the number of false negatives.

TABLE I
CLASSIFYING LEVEL OF ACCURACY BASED ON AUC

AUC value	Classified as
0.90 – 1.00	Excellent
0.80 – 0.90	Good
0.70 - 0.80	Fair
0.60 – 0.70	Poor
0.50 – 0.60	Fail

III. EXPERIMENT AND RESULT

All the experiments were conducted in Matlab Ver 7.1 by using a PC Intel-Pentium Centrino with RAM 1 GB.

A total of 53 cyst lesions and 80 tumor lesions measuring 40x40 pixels are transformed into first-order statistics texture. Based on first-order statistics, 6 texture features was extracted.

TABLE II
TABULATED MINIMUM AND MAXIMUM FEATURES VALUE FOR CYST AND TUMOR CLASSIFICATION EXTRACTED FROM FIRST-ORDER STATISTICS TEXTURE

Features	Cyst Lesions		Tumor Lesions	
	Min.	Max.	Min.	Max.
Mean	13.7650	213.2888	85.0038	252.3044
Standard deviation	0.5163	3.3309	0.4383	3.6734
Smoothness	0.8377	0.9709	0.8142	0.9735
Third moment	-0.0334	0.2369	-0.6272	0.2748
Uniformity	0.0110	0.1246	0.0086	0.4602
Entropy	4.2028	6.7591	2.4005	7.0271

Table II shows the features' values extracted from first-order statistics texture for both lesions. It can be seen that the value of the features both classes are overlapping, which makes a perfect linear separation impossible but the minimum and maximum value for both classes are different. This shows that classification process cannot be easily done (not linear) because the overlapping value. But the difference in each class maximum and minimum features' value makes classification still possible to conduct (non linear classification). For example, the mean values of cyst lesion are from 13.7650 until 213.2888 while the mean values of tumor lesion are from 85.0038 until 252.3044. This problem is handled by SVMs in the nonlinear case. SVMs maps the original data points from the input space to a high dimensional feature space (see Fig. 2). We use one third hold out cross validation of 133 data images by randomly selecting 94 images referring to each class as data training, while the rest (39 images) was used for the data test. The experiments were conducted 20 times. Using SVM with kernel Gaussian and parameter value C = 10000, α = 1e-7 and γ = 4000, we get accuracy up to 84.62 % and the average value is 72.31 %. Using ROC curve (see Fig. 3) and computing the AUC, we get the AUC up to 0.9361 and the average value is 0.8347. This means that the cyst lesions and tumor lesions can be distinguished. We have achieved the excellent classifying level of accuracy. (see Table I)

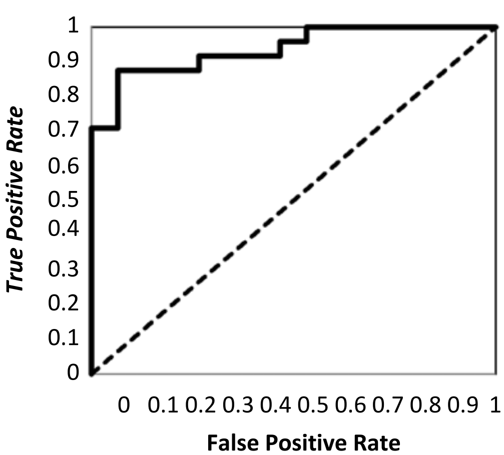

Fig. 3. ROC Curve with AUC value of 0.9361

IV. DISCUSSION

In this study, we observed that the texture features can be used to classify cyst and tumor lesions. Texture is one of the important characteristics used in identifying objects or ROI in an image [11]. Table II shows that there is an overlap value between the features data for cyst and the features data for tumor. Thus, linear classification is impossible to be implemented. SVM can be used to separate this data using kernel function. The result shows that choosing kernel and its parameter are important to classify the features of lesion. In this study, we use Gaussian Kernel with C= 10000, α=1e-7, γ = 4000 that yield the best result.

Performance of accuracy evaluation by statistical prediction model can also be done by ROC (Receiver Operating Characteristics) curve analysis. ROC curve is a graphical plotting with the y-axis express sensitivity (true positive rate) and the x-axis express false positive rate [16–18]. This method achieved very good accuracy (up to 84.62 % and the AUC value of 0.9361.

V. CONCLUSION

Based on experimental results, it concludes that texture features based on first-order statistics texture can be used to distinguish between cyst and tumor lesion on dental panoramic image, with accuracy levels up to 84.62 %, and AUC value of 0.9361.

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