Diagnosing Interdental Decays in Mouth Radiography Images using Kernel Fuzzy C means Segmentation and Cascade Object Detector

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Abstract

Mouth radiography is one of the common ways of diagnosing tooth decays. Especially for interdental decays which are hard to be examined by naked eyes. In this paper, we present a method for diagnosing internal decay in real word mouth radiography images, which have been gathered in Tabirz Sina dental clinic. Firstly, we will use Kernel Fuzzy C-Means (KFCM) algorithm, which is modifying the objective function in the fuzzy C-means algorithm using a kernel-induced distance metric, as an image segmentation method. Then, the processed images are labelled with decay and are then employed to a cascade object detector for diagnosing purposes. In order to show the efficiency of the employed method the performance is tested on testing mouth radiography image data set. The results indicate that this method composed of KFCM and cascade object detector structures is successful in detecting interdental decays.

1. Introduction

Mouth radiography is one of the common ways of diagnosing tooth decays. Especially for interdental decays which are hard to be examined with naked eyes. [1]. Many a time researchers have reported that digital images have no diagnosing privilege in interdental decays over a normal radiographic film [2-6]. Most of these researches have shown that the diagnostic accuracy of a normal film and a digital image is comparable, so improving digital images for better interdentally decays diagnosis have been studied [4-7]. Although some researchers have shown that improving digital image can increase the accuracy of decay diagnosis, most of them have shown weak diagnosis in primary decay in digital films and images [3]. In recent years, with the increasing size and number of medical images, the use of different computers techniques have facilitated their processing [8-12]. Image segmentation is one of important technique in medical image. In particular, as a task of delineating anatomical structures and other regions of interest [11]. Image segmentation algorithms play a vital role in biomedical imaging applications such as the quantification of tissue volumes, diagnosis, and treatment planning [10]. Image segmentation is defined as important step in the partitioning of an image into non-overlapping, constituent regions, which are homogeneous with respect to some characteristics such as intensity or texture [8].

In this study, to overcome the problem of diagnosis decays in mouth radiography images, we propose a new method to detect and diagnose interdental decays in mouth radiography. In our proposed method, we use and employ the Kernel Fuzzy C-Means (KFCM) clustering approach [16] as the image segmentation method. Then, the processed images are labelled with decay and are then employed to a cascade object detector [18] for diagnosing purposes. The general flow chart of the developed method for diagnosing internal decay is given in Fig.1. As it can be observed from Fig.1, in the first stage, we segmented all images with KFCM algorithm into two-cluster .In the second stage, we labelled the tooth decays and then train a cascade object detector. In this study, 75% of the real word mouth radiography image data set has been used as training data and the rest as testing data. The presented results show that the proposed method composed of KFCM and cascade object detector structures is an efficient way to diagnose tooth decays, especially interdental decays.

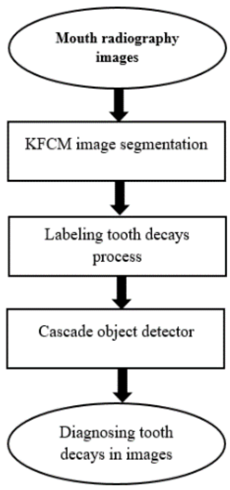

Fig. 1. The proposed method for diagnosing decays

The paper is organized as follows. Section 2 presents the kernel fuzzy c means image segmentation method for our data. Section 3 explain labelling tooth decays process and cascade object detector structure to detect the decays in our image. Section 4 presents the results of cascade object detector and discussions. Finally, in Section 5 presents conclusions.

2. Kernel Fuzzy C Means Algorithms

Fuzzy C-means (FCM) clustering is an efficient way to form of clusters in data sets as each data point can belong to more than one cluster [17]. The fuzzy clusters are identified via similarity measures [14]. These similarity measures include distance, connectivity, and intensity. Membership grades are assigned to each of the data points. These membership grades indicate the degree to which data points belong to each cluster [13]. Thus, points on the edge of a cluster, with lower membership grades, may be in the cluster to a lesser degree than points in the center of cluster.

The FCM have are many advantages, However, there are also some disadvantages; one of them is the Euclidean distance. The Euclidean distance measures can unequally weight underlying factor [29]. It make the FCM algorithm cannot handle the small differences between clusters. To overcome this disadvantage in our study, we will use the KFCM. The kernel method maps nonlinearly the input data space into a high dimensional feature space [21]. The essence of kernel-based methods involves performing an arbitrary non-linear mapping from the original d-dimensional feature space R^d to a space of higher dimensionality (kernel space) [23]. The kernel space could possibly be of infinite dimensionality. The rationale for going to higher dimensions is that it may be possible to apply a linear classifier in the kernel space while the original problem in the feature space could be highly nonlinear and not separable linearly. The kernel method then takes advantage of the fact that dot products in the kernel space can be expressed by a Mercer kernel [23]. Thus, the distance in the kernel space does not have to be explicitly computed because it can be replaced by a kernel function.

Given, X=$\{x_1, \dots x_n\} \in \mathrm{R^d}$, the FCM partitions X into c fuzzy subsets by minimizing the following object function

$$E = \sum_{j=1}^{C}\sum_{i=1}^{N} \mu_{ij}^{m} \left\|X_i - C_j\right\|^2 \qquad (1)$$

where N is the number of pixels in each image, C is the number of clustering center, μ_{ij} is the fuzzy membership of sample (pixel) x_i and the cluster identified by its center c_j, and m is a constant that defines the fuzziness of the resulting partitions. The parameter m is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. Large values of m will blur the classes and all elements tend to belong to all clusters also small values of m will be change fuzzy C means algorithms to k-means clustering[17].

We use the Gaussian kernel function for simplicity. Now consider the proposed Gaussian kernel fuzzy c-means algorithm. Define a nonlinear map as (2).

$$\emptyset : x \to \emptyset(x) \in F \qquad (2)$$

where $x \in X$ denotes the data space, and F the transformed feature space with higher even infinite dimension. In KFCM, we minimizes the following objective function (3).

$$E = \sum_{j=1}^{C}\sum_{i=1}^{N} \mu_{ij}^{m} \left\|\emptyset(x_i) - \emptyset(c_j)\right\|^2 \qquad (3)$$

$$\left\|\emptyset(x_i) - \emptyset(c_j)\right\|^2 = K(x_i, x_i) + K(c_j, c_j) - 2K(x_i, c_j) \qquad (4)$$

where $K(x,y)=\emptyset(x)^T\emptyset(y)$ is an inner product kernel function. If we adopt the Gaussian function as a kernel function, i.e. $K(x,y)=exp(\|x-y\|^2/\sigma^2)$,then $K(x,x)=1$ according To (3), (4), the objective function can be rewritten as (5).

$$E = 2\sum_{j=1}^{C}\sum_{i=1}^{N} \mu_{ij}^{m}\left(1 - k(x_i, c_j)\right) \qquad (5)$$

In image clustering, the most commonly used feature is the gray level value, or intensity of image pixel [16] .Thus the KFCM objective function is minimized when high membership values are assigned to pixels whose intensities are close to the centroid of its particular class, and low membership values are assigned when the point is far from the centroid. Minimizing (5) under the constraint$\sum \mu_{ij} = 1$, we have

$$\mu_{ij} = \frac{\left(1 - K(x_i, C_j)\right)^{1/(m-1)}}{\sum_{j=1}^{c}\left(1 - K(x_i, C_j)\right)^{1/(m-1)}} \qquad (6)$$

$$C_j = \frac{\sum_{i=1}^{n} \mu_{ij}^{m} k(x_i - C_j) x_i}{\sum_{i=1}^{n} \mu_{ij}^{m} k(x_i - C_j)} \qquad (7)$$

The KFCM algorithm for each of mouth radiography image can be summarized in the following steps. [24]

Step 1) Initialize the cluster centers Cj and let t = 0.
Step 2) Initialize the membership's functions μ_{ij} according (6).
Step 3) For $t = 1, 2, \dots, t_{max}$, m=2 do:
(a) Update all prototypes C_j with (7).;
(b) Update all memberships with (6).;
Step 4: Repeat Steps 2 to 3 until convergence (t_{max}=100).

The images segmentation implemented with Matlab R2016b. The sample original image is given in Fig.2 and segmented image is given in Fig.3. In the segmented images, interdental decays specify with white colure in KFCM images .However each white area are not known as tooth decays.

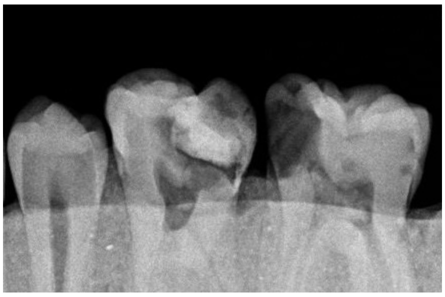

Fig. 2. Sample 1 Original image

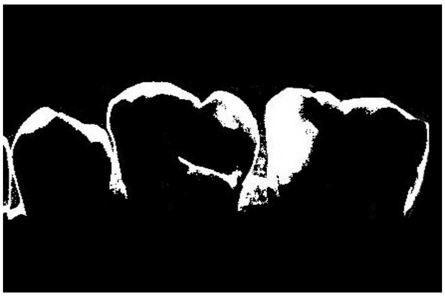

Fig. 3. Sample 1 KFCM segmentation

In dentistry, the restored teeth, consider as a healthy teeth. For instance in other original sample, which is given in Fig.4 the second teeth, restored from the top and is correctly segmented with KFCM algorithm.

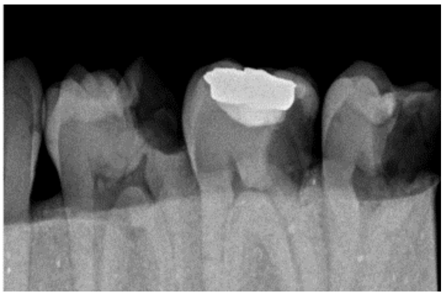

Fig. 4. Sample 2 Original image

Fig.5. Sample 2 KFCM segmentation

3. Cascade object detector

Usually the image is first processed on a lower level to enhance picture quality. Then the picture is processed on a higher level, for example detecting patterns and shapes, and thereby trying to determine, what is in the picture [19]. In our proposed method according to the specification of mouth radiography image to achieve a good result, we use KFCM clustering approach as the image segmentation method to enhance images and remove the noise in our radiography images. After it, we can use a computer vison toolbox in Matlab to design a cascade detector to diagnosing interdental decays in image, which were acquired at the previous stage. The work with a cascade classifier includes two major stages: training and detection [22]. Cascade classifier training requires a set of positive samples and a set of negative images. We must provide a set of positive images with our regions of interest specified to be used as positive samples. For this purpose, we use a training image labeller application in Matlab to label interdental decays in each mouth radiography image .We training only correct white area as a decays in this image labeller application .The Training Image Labeller outputs a table to use for positive samples. We do this process for labelled 75 percent of our images. The samples training images, which are labelled with training labeller application, are given in Fig.6 and Fig.7.

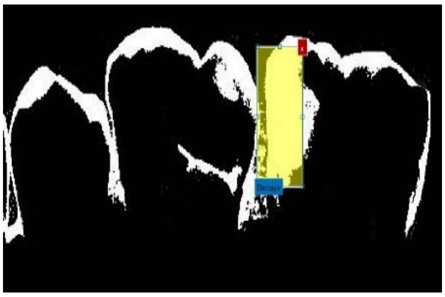

Fig. 6. Sample training image, which is labelled with training labeller application

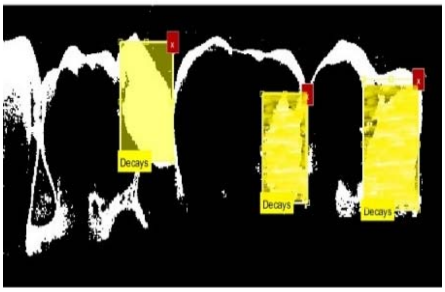

Fig. 7. Sample training image, which is labelled with training labeller application

We provide a set of negative mouth radiography images which do not have tooth decay. After the classifier is trained, it can be applied to a region of an image and detect the object in mouth radiography images. The cascade classifier consists of a list of stages, where each stage consists of a list of weak learners [18]. The system detects objects in question by moving a window over the image [19]. Each stage of the classifier labels the specific region defined by the current location of the window as either positive or negative, positive meaning that an object was found or negative means that the tooth decays was not found in the image [22]. If the labelling yields a negative result, then the classification of this specific region is hereby complete and the location of the window is moved to the next location. If the labelling gives a positive result, then the region moves of to the next stage of classification [22]. The classifier yields a final verdict of positive, when all the stages, including the last one, yield a result, saying that the object is found in the image. The general structure of our cascade object detector can be shown in Fig .8.

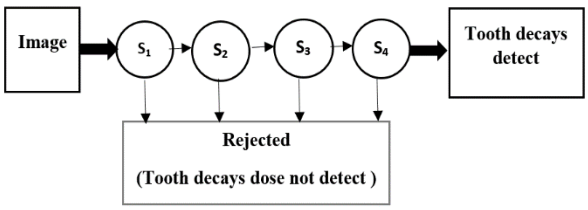

Fig. 8. The classifier cascade architecture

The stages are designed to reject negative samples as fast as possible [16]. The assumption is that the vast majority of windows do not contain the object of interest. Conversely, true positives are rare and worth taking the time to verify [18]. In order to achieve the best performance in cascade object, always have a trade-off between classification accuracy and speed of cascade object detector. In this study, to reach the best results, we consider four stage with lower false positive rate for each stage in our cascade object detector.

4. Performance Analysis and Results

The experiments and performance evaluation have performed on our mouth radiography images with computer vison toolbox in Matlab 2016b. We have implemented cascade object detector for all our test image. The sample result of cascade object detector in diagnosis decays are given in Fig11 and Fig14.

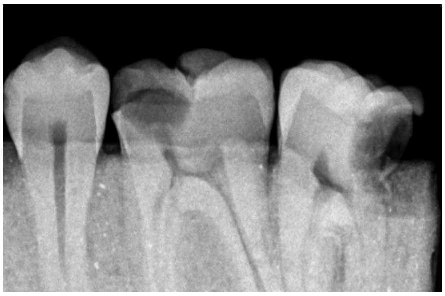

Fig.9. Test Sample 1 Original image

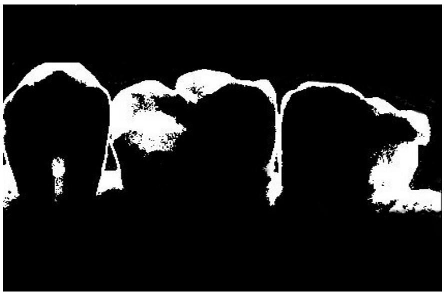

Fig.10. Test Sample 1 after Segmentation

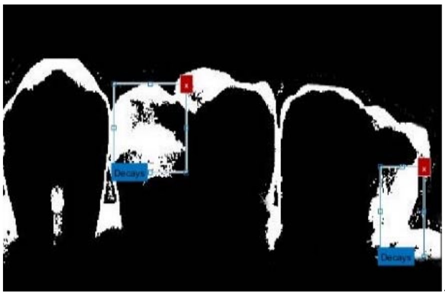

Fig.11. Result of diagnosing interdental decays in test 1

In the Fig.11 cascade object detect accurately detect two interdental decays in our test image. However, sometime cascade object detector in diagnose the number of the decays have some errors. For instance in the sample 2 original image exit two interdental decays, although, the cascade object detector diagnose three interdental decays which is shown in Fig14.

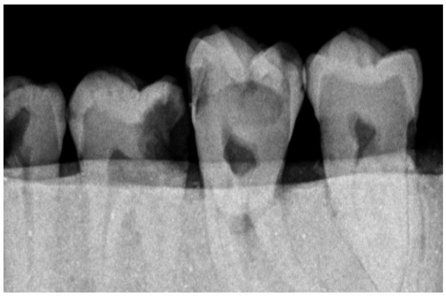

Fig.12. Test Sample 2 Original image

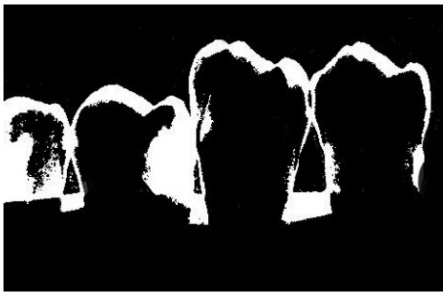

Fig.13. Test Sample 2 after Segmentation

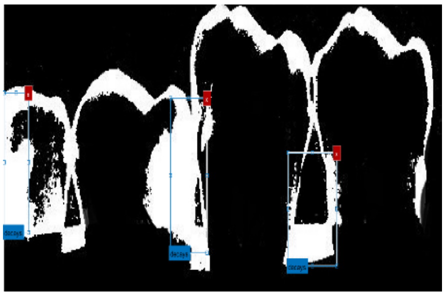

Fig.14. Result of diagnosing interdental decays in test 2

In this study, we use 97 images for training and 33-image use as a test image with 62 interdental decays. The performance of our cascade object detector in mouth radiography test images in diagnosing the decays are given in Table 1.

Table 1. Performance of our proposed method

		Cascade object detector result	
		negative	positive
Actual result	negative	2 3.22 %	6 9.67 %
	positive	6 9.67 %	48 77.44 %

As you can see in Table.1 the accuracy of our cascade object detector in diagnosing tooth decays estimate as 77.44 %.To sum it up the performance of our proposed method for two classes are 80.66 %.

5. Conclusions

Diagnosing tooth decays is very important part in dental treatment, usually interdental decays are hard to be examined by naked eyes, and it is difficult to detect it from the mouth radiography images. The aim of this paper is to propose a new method in diagnosing tooth decays using KFCM segmentation and cascade object detector. We use KFCM as clustering approach to enhance images and remove the noise in our radiography images .The advantage of KFCM in use the effect of neighbour pixel information cause to improve the clustering accuracy of an image. In this study, we training and applied cascade object detector to find the interdental decay in mouth radiography images. The presented results show that the proposed method composed of KFCM and cascade object detector structures is successful in detecting interdental decays in moth radiography images. It can be useful in some fields like medical image analysis, such as tumour detection, and treatment planning.

6. References

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