Detection of occlusal caries based on digital image processing

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Abstract—**The aim of this work is to present an automated non supervised method for the detection of occlusal caries based on photographic color images. The proposed method consists of three steps: (a) detection of decalcification areas, (b) detection of occlusal caries areas, and (c) fusion of the results. The detection process includes pre-processing of the images, segmentation and post-processing, where objects not corresponding to areas of interest are eliminated through the utilization of rules expressing the medical knowledge. The pre-processing, segmentation and post-processing are differentiated depending on the areas that have to be detected (decalcification or occlusal areas). The method was evaluated using a set of 60 images where 286 areas of interest were manually segmented by an expert. The obtained sensitivity and precision is 92% and 80%, respectively.**

I. Introduction

DENTAL caries is an irreversible microbial disease of the calcified tissues of the teeth, characterized by demineralization of the inorganic portion and destruction of the organic substance of the tooth, which often leads to cavitation [1]. Caries can be detected in three different sites of the tooth: (a) pit and fissure caries, (b) smooth surface caries, (c) root surface. The pit and fissure caries (occlusal caries) represent the most common type of cavities. It is indicative the fact that the occlusal surfaces of teeth represent 12.5% of all tooth surfaces, however, is the location of over 50% of all dental caries [2].

Occlusal caries has become relatively more important, due to the changing pattern of dental caries that has occurred in the last decades. It might be expected that occlusal caries would be fairly easy to diagnose, because unlike approximal and subgingival root surfaces, these surfaces are readily accessible for visual inspection. However, clinically or radiographically, diagnosis of occlusal lesions is a delicate problem, because of the morphology of the occlusal surface. More specifically, the complicated three-dimensional shape of the occlusal surfaces, incorporating fossae and grooves with a great range of individual variations, convert the diagnosis of occlusal caries to a difficult task for the clinicians. Diagnosis consists of two basic steps. First, the detection of carious lesion and then the assessment of the patient's caries risk.

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A common approach, followed in clinical practice for the detection of occlusal caries, is visual inspection. The clinician relies, mainly, on visual observation of texture and discoloration. Detailed criteria for visual inspection of occlusal surfaces have been developed and presented in the literature [3]. Visual-tactile is another conventional method of dental examination. The dentist detects the presence of caries and diseases in the mouth via sight (visual inspection) or touch (usually using a dental explorer). However, the clinical assessment, performed using visual or visual-tactile methods, is subjective, since it is based on the experience of the clinician. The variance of the assessments between clinicians leads to different approaches for the management of carious lesions [4, 5].

Enhanced visual techniques have also been utilized for the detection of occlusal caries. These include fiber optic transillumination, laser or light fluorescence, digital radiography and electrical resistance [4, 5]. Although the systems mentioned above allow the visualization of the demineralization, which cannot be seen visually, the low performance of all of these systems leads the experts to utilize the above detection systems to augment their diagnosis. For these reasons the development of computer aided caries detection methods gained the interest of the researchers.

Umemori *et al.* [6] processed and analyzed digital photographs using image processing software. The area of occlusal surface (OSA), of pit and fissure discoloration (PFA) and the proportion of the PFA to the OSA was calculated. The image of depicting the pit and fissure discoloration was converted to binary and its fractal dimension (FD) was computed. Finally, two-way ANOVA and Games-Howell test were used in order to reveal differences in the calculated metrics between each clinical diagnosis. Kositbowornchai *et al.* [7] developed a neural network to diagnose artificial dental caries using images from a charged coupled device (CCD) camera and intra-oral digital radiography. Olsen *et al.* [8] processed digital color images using the Directed Active Shape Modeling (DASM) algorithm in order the tooth and drilled preparation to be segmented. Seven features, gradient of the color image and six texture measures, were then extracted, and were the input of the classification algorithm which identifies pixels that represent areas of the tooth surface that are damaged by caries. For the classification five classifiers were employed.

In this work, we propose an automated non supervised method for the detection of occlusal caries areas. The method is based on the segmentation of photographic color

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images. More specifically, the *k*-means algorithm is applied to the color image for the segmentation of the decalcification areas (DA), while occlusal caries areas (OCA) are detected through the application of image processing operations to each channel (red, green, blue) of the color image. For each detected area features expressing the shape and the texture of the area are extracted. Finally, the combinations of the extracted features through rules, which express medical knowledge, are applied in order areas that correspond to false positives to be eliminated. The images were annotated by one expert and the method was evaluated in terms of sensitivity and precision. The proposed method is differentiated from those reported in the literature since it does not require the intervention of the experts, it is unsupervised, it does not need the patient to be subjected to imaging examination (e.g. X-ray).

II. MATERIALS AND METHODS

A. Dataset

We have collected 60 digital color images (6 *in vivo* images and 54 *in vitro* images). The *in vivo* images were recorded using a Canon Rebel XTi 10.1 MP digital camera, with lense Canon Macro EF 100mm 1:2.8 USM, flash Macro Ring Light MR14 EX and magnification 1:1. The *in vitro* images were recorded using Olympus E-500 Digital 8MP with lense Olympus digital 50mm macro plus an Olympus 2x Teleconverter (EC-20) giving a magnification almost 1:2. The speed was set at 1/125sec and diaphragm at F45 stop at 0.79m focusing distance. The ring flash is a Starblitz (Macrolite-1000 Auto). The images were annotated by one expert. The expert outline the perimeter of the decalcification and occlusal caries areas using a software developed in MATLAB v7.12. In the dataset 286 regions of interest were identified.

B. The automated method

The proposed method consists of three steps: (a) detection of DA, (b) detection of OCA, and (c) fusion of the results of the two previous steps. The detection process for the two different areas of interest runs in parallel. The detection process includes the following procedures, which are differentiated depending on the area of interest (decalcification or occlusal caries): (a) preprocessing of the photographic color images, (b) segmentation of areas of interest, (c) feature extraction and (d) object elimination.

C. Detection of decalcification areas

The color image is converted to gray scale intensity image (Im) by eliminating the hue and saturation information while retaining the luminance. More specifically, the RGB values are converted to grayscale values by forming a weighted sum of the R, G and B components using the following formula [9]:

$$Im(x,y) = 0.2989 * R + 0.5870 * G + 0.1140 * B, \qquad (1)$$

where R, G and B are the pixel (x,y) value of the red, green and blue channel, respectively. The intensities of the gray scale image is rescaled to the range [0, 1] and then the contrast of the image is adjusted by applying the following sigmoid function [10]

$$newIm(x,y) = 1/(1 + e^{gain*(c-Im(x,y))}), \qquad (2)$$

where $newIm(x,y)$ is the value of the pixel (x,y) of the image after the application of the sigmoid function, $gain$ controls the actual contrast, c represents the (normalized) grey value about which contrast is increased or decreased and $Im(x,y)$ is the value of the pixel (x,y) of the image before the application of the sigmoid function.

The image ($newIm$) is converted to binary. The threshold for this conversion is determined by employing Otsu's method [11]. In the image obtained in the previous step neighboring pixels with connectivity eight are grouped together to create the objects depicted in the image. For this purpose the procedure outlined in [12] is applied. If the detected objects are more than one, we compute the area of the objects. The largest obtained object is the tooth region, whose empty areas are filled using the flood fill algorithm [13]. The perimeter of the tooth is extracted. A pixel belongs to the perimeter of the tooth if its value is equal to one and it is connected to at least one zero-valued pixel. The perimeter is used for the computation of the center of the tooth. More specifically, the bounding box, the smallest rectangle containing the region of the tooth, is created and the coordinates of the bounding box area are used for the calculation of the center of the tooth.

For the segmentation of the image *k*-means clustering algorithm [14] is employed. The *k*-means algorithm treats each object as having a location in space. It finds partitions such that objects within each cluster are as close to each other as possible, and as far from objects in other clusters as possible. It requires that you specify the number of clusters to be partitioned and a distance metric to quantify how close two objects are to each other. In our case the number of clusters is 3 and the Euclidean distance is used as a distance metric. The number of clusters is set equal to 3 (decalcification area, area of the tooth and background) since, according to our expert, no other pathological conditions on the tooth are presented. The clustering is repeated three times in order local minima to be avoided. The *k*-means returns an index corresponding to a cluster which is used in labeling every pixel in the image with its cluster index.

The pixel labeling is the input of the cluster selection approach. Based on pixel labeling three new images are created each one corresponding to a different cluster. Then, the area of objects belonging to each cluster is computed. The cluster with the minimum total area is selected as the one that depicts the objects that correspond to decalcification since the other two clusters mainly depict the area of the tooth and the background.

The DA are recognized as small white areas that are near or adjacent to the fissures of the tooth. In order these characteristics to be expressed features, describing the area, the shape and the position of the objects detected in the previous step, are extracted. More specifically, the area, eccentricity and centroid are computed.

The elimination procedure takes into account the features extracted in the previous step. Since the DA are small in size objects, all objects with area larger than 13000 or smaller than 100 pixels are removed. The fact that regions of interest (ROIs) are adjacent to fissures of the tooth implies that ROIs have line shape. For this purpose objects with eccentricity lower than 0.6 are eliminated. Finally, the observation that the fissures of the tooth start from the center and propagate to the perimeter of the tooth leads to the elimination of objects having Euclidena distance of their centroid from the center of the tooth larger than 300.

D. *Detection of occlusal caries*

The earliest sign of a new carious lesion is the appearance of a chalky white spot on the surface of the tooth, indicating an area of demineralization of enamel. As the lesion continues to demineralize, it can turn brown but will eventually turn into a cavitation (dark brown to black). Dark brown regions surrounded by regions with different colorations of brown are a common finding in the occlusal surface of the tooth when dental caries exist. These regions of discoloration of the tooth can be detected by the three channels of the color image. More specifically, dark brown regions can be detected by the red channel, lighter brown regions can be detected from the green channel, while regions in the first stages of discoloration can be detected from the blue channel. For this reason the detection of the OCA are applied to red, green and blue channel of the color image seperately. The results obtained from the three channels are fused.

From the initial color image the red, green and blue channel are assigned to different images, red_im, $green\_im$, $blue\_im$, respectively. Each one of these images are converted to binary by applying a theshold computed from the Otsu's method [11].

For the segmentation of OCA the following procedure is applied. First, the mask of the tooth that was created in the first step of the proposed mehtod is applied to the binary image from the previous step, in order artefacts presented in the background of the image to be removed. Then the perimeter of the depicted objects is extracted. Finally, the perimeter of the tooth is removed.

The elimination of the objects corresponding to occlusal caries is achieved by applying rules concerning the area of the object and their distance from the perimeter of the tooth and from the center. More specifically, objects with area lower than 30 or greater than 900 pixels are eliminated. The intensity of pixels of objects that are close to the perimeter of the tooth region, is set equal to zero using morphological operators. The dilation operation (with a squared structure element whose width is 10 pixels) is applied on the image of the perimeter and then the resultedimage is projected on the image that depicts the occlusal caries objects. Finally, objects with distance lrger than 1000 pixels from the center of the tooth are eliminated. It must be mentioned that that the application of the rules is made sequentially with the order reported above.

The objects that remain from the previous step from each channel of the color image are projected to the same binary image. In order to address the fact that the boundaries of the same region of interest are differentiated depending on the channel of the color image the logical operator AND is applied between the images of the different channels. More specifically, the operator AND is applied between the red and green channel and it detects the objects which are depicted in the red channel and overlap with objects depicted in the green channel. The operator AND is then applied one more time between the image of the previous step and the blue channel.

E. *Fusion of the results of the two detection processes*

The detected objects that correspond to DA and the detected objects that correspond to occlusal caries are projected to the same binary image. The centroids of the depicted regions are computed. The distance between the centroids of the DA with each one of the centroids of the occlusal caries regions is computed. If the distance is greater than 320 pixels, the corresponding decalcification regions is eliminated. The application of this rule aims to retain only the decalcification objects that are close or surround occlusal caries objects. Finally, texture features are calculated. If the average contrast is lower than the mean average contrast of all objects the object is removed. The remainig objects are projected to the initial image.

III. RESULTS

The proposed methods was evaluated using the dataset described in Section II.A. The method is applied to each one of the 60 images and the regions of interest (occlusal caries and DA) are segmented. In Fig. 1 the results of the automated segmentation and the corresponding results of manual segmentation are presented. The total number of regions of interest identified by the physician in the dataset is 286. Our method has detected 264 regions (true positives). The number of false negatives is 22 and the number of false positives is 65 (25 due to the detection process of occlusal caries and 40 due to the detection process of the DA). This results in sensitivity 92% and precision 80%.

One expert have manually detected regions of interest. The regions were outlined using a software developed in MATLAB v7.12. The user picks the pixels that constitute the perimeter of the regions of interest. The coordinates of those pixels are recorded to a text file. Once the selection of the pixels is completed, the border of the polygonal region of interest is created within the image. For this purpose the *roipoly* Matlab function is utilized. The *roipoly* function takes as input the image of interest, displays the image on the screen and lets the user specify the polygon using the mouse. Once the selection of points is completed, it draws the selected polygon on the image [9]. The border of each region has a color representing the classification of the specific region provided by the expert (*yellow*-sound, *green*-first visual change in enamel, *cyan*-distinct visual change in enamel, *magenta*-localized enamel breakdown, *blue*-underlying dentine shadow, *red*-distinct cavity with visible dentine, *black*-extensive cavity within visible dentine). The classification was made according to the International Caries Assessment and Detection System (ICDAS) criteria [3].

The regions not detected by the proposed method (Fig. 2) correspond mainly to pit and fissures of the tooth that, according to the assessment of the expert, are either sound or in an early stage of decay. It must be noted that in some cases a part of the region is detected (the darker one). The not correctly identified regions (Fig. 3) are mainly regions of the tooth where the flash of the camera is reflected. This is also observed on images received under *in vivo* conditions.

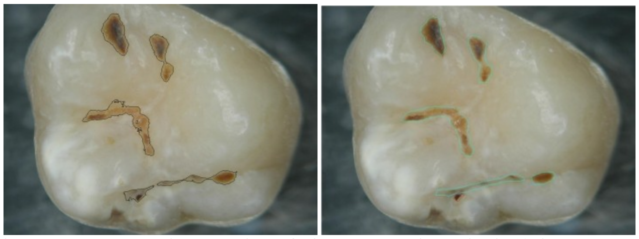

Fig. 1. Segmentation results of the proposed method (*left:* proposed method, *right:* manual segmentation).

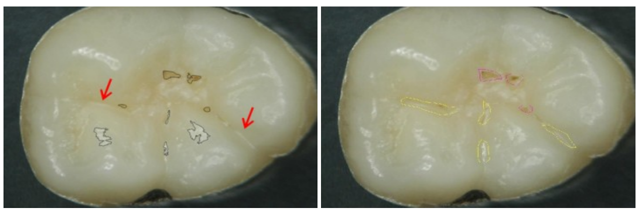

Fig. 2. Regions not detected by the proposed method (indicated by the red arrow, *left:* proposed method, *right:* manual segmentation).

Fig. 3. Regions not correctly detected by the proposed method (outlined with red color, *left:* proposed method, *right:* manual segmentation).

A comparison of the proposed method with those reported in the literature is presented in Table I. According to the results the sensitivity of the proposed method is 3% and 11% better than those reported by Umemori *et al.* [6] and Kositbowornchai *et al.* [7], respectively. The comparison of the proposed method with the one reported by Olsen *et al.* [8], in terms of accuracy (accuracy is defined as the percentage of true results), reveals the predominance of the proposed method per 8% at least.

IV. CONCLUSIONS

We presented an automated method for the segmentation of occlusal caries using photographic color images. The method employs three components: detection of DA, detection of OCA and fusion of the results. We tested our method in a dataset of 60 images with satisfactory results. The achieved sensitivity is 92% and the precision is 80%. Although the achieved performance is satisfactory the reduction of false positives, through the optimization of the thresholds utilized in the elimination procedure, and the classification of the cavitations according to ICDAS will be addressed in the future.

TABLE I
COMPARISON OF THE PROPOSED METHOD WITH OTHER METHODS EXISTING IN THE LITERATURE

Method		Sensitivity	Specificity
Kositbowornchai *et al. 2006*	CCD camera	77%	85%
	Digital Radiograph	81%	93%
Umemori *et al. 2010*	FD	89%	84%
	PA	47%	95%
	DD	69%	91%
	FD and PA	86%	86%
Method			Accuracy
Olsen *et al. 2010*	RBF	With PCA	84%
		Without PCA	74%
	Sensitivity	Precision	Accuracy
Proposed method	92%	80%	92.3%

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