Quantification of Pigmented Regions in Detracted Images

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This study presents a method for analyzing and quantifying pigmented areas on dental surfaces after the application of caries detection products. The methodology integrates image enhancement, the creation of binary masks, and conversion to the HSV color space to isolate and accurately calculate the extent of pigmentation. A dataset consisting of 200 images of unpigmented teeth and 200 images of pigmented teeth was used, with strict criteria for selecting images that provided a clear frontal view, focusing on the upper and lower canine regions. The image processing steps included using LabelMe software for manual annotation and applying binary masks to segment the teeth from the background. Specific color filters identified pigmented regions. Histogram analysis in the HSV space validated the predominance of red shades corresponding to the pigmented areas, confirming the accuracy of the segmentation. The results demonstrate the effectiveness of the proposed method for calculating pigmented areas, providing an objective measure that can be used to assess the efficacy of products designed for bacterial plaque detection in dental applications.
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The early detection of bacterial plaque is essential for ensuring oral health and preventing the progression of lesions that may compromise dental structures. Bacterial plaque is a biofilm that forms on the surface of teeth and is a primary factor in the development of cavities and periodontal diseases. Effective detection methods can assist oral health professionals in making more precise clinical decisions and implementing less invasive treatment strategies [1].

Historically, bacterial plaque identification has been performed through visual examinations, often aided by specific dyes that reveal the presence of plaque on dental surfaces. These dyes, such as red acid and iodine-povidone, bind to demineralized areas, highlighting lesions that may not be visible to the naked eye. However, these methods have limitations, including the subjectivity of result interpretation and the high cost of materials, which may hinder their large-scale use [1].

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Accuracy in detecting and monitoring bacterial plaque is crucial for early intervention and the continuous assessment of oral health. Failure to correctly identify plaque can lead to inadequate treatments, resulting in lesion progression and tooth loss. Thus, searching for more accessible, precise, and automated detection methods is very important for clinical dental practice [2].

Dental image segmentation is a critical step in quantifying bacterial plaque in imaging technologies and data processing. Segmentation involves extracting regions of interest, such as the pigmented tooth area, to ensure that subsequent area calculations are representative and reliable. Segmentation techniques range from simple threshold-based methods to advanced deep learning algorithms, such as convolutional neural networks [3].

However, dental image segmentation faces several challenges. Anatomical variability, such as differences in tooth morphology and surrounding structures, can complicate the application of standardized segmentation models. Additionally, the quality of captured images, especially in clinical environments with equipment of varying quality levels, can affect the accuracy of segmentation algorithms [3].

Panoramic radiographs, for example, are widely used in dentistry because they provide a comprehensive view of the dental arch. However, segmenting individual teeth in these images is challenging due to the overlapping of structures and low resolution in some areas, which may compromise the precise identification of regions of interest [4].

Given these challenges, this study focuses on precisely quantifying the pigmented area in teeth after applying dyes. The proposal is to use advanced segmentation techniques to isolate the areas of interest and calculate the extent of pigmentation to improve the assessment of dye efficacy in bacterial plaque detection. This approach seeks to contribute to clinical practice and the development of automated tools that can be applied on a large scale, reducing costs and increasing the accessibility of detection methods [4].

Related Work

Tooth detection in medical images is a significant challenge due to teeth' morphological diversity and variations in image capture conditions. Several recent studies have explored innovative approaches to improving the accuracy and efficiency of this process, contributing to important advancements in the field.

Guo and colleagues [5] proposed an innovative method using Mask R-CNN with an attention mechanism for detecting abnormal teeth in dental X-ray images. This study stood out for improving detection accuracy and increasing diagnostic efficiency, achieving 79% accuracy. The application of Mask R-CNN proved effective in handling the complexity of the images, offering a promising solution for automatically detecting dental anomalies.

On the other hand, Sirinat and colleagues [6] explored tooth identification through a rotation-based correlation method. Although the approach showed potential, the lack of data on the effectiveness of the results suggests that further studies are needed to validate its application in different clinical contexts. This study emphasizes the importance of developing and testing new methods to ensure their robustness and applicability in practical scenarios.

Another relevant study is from Samiappan and colleagues [7], that applied Convolutional Neural Networks (CNNs) for tooth detection in radiographs of the lower and posterior regions of the mouth. This approach successfully segmented teeth and identified possible fractures, demonstrating the versatility of CNNs in different clinical contexts. The accuracy in fracture identification highlights the importance of CNNs in complex diagnoses, where precise segmentation is crucial for proper treatment.

Finally, Kong and colleagues [8] presented a two-stage approach with region-of-interest exclusion, achieving 0.76% accuracy in periodontitis classification. This study underscores the challenges faced in dentistry, particularly in detecting periodontal diseases, and the need for specialized approaches to improve diagnostic accuracy. The two-stage methodology offers a promising strategy for dealing with complex clinical cases where simple segmentation may not be sufficient for an accurate diagnosis.

Materials and Methods

Database

This study was conducted using two distinct datasets: a public database and a set of colored tooth images captured after the application of products for cavity identification. The public database includes 200 images of properly labeled non-pigmented teeth, while the pigmented database contains 200 images, of which 30 were classified in detail. The selected images provided a clear frontal view of the teeth, focusing on the region between the upper and lower canines, ensuring consistency for subsequent analyses.

Tooth Segmentation

Tooth segmentation was performed using the LabelMe software to manually label regions of interest in each image. LabelMe is a widely used image annotation tool developed by MIT in the computer vision community. This tool facilitates the creation of annotated datasets for tasks such as object detection, image segmentation, and scene recognition, allowing for precise annotation of regions of interest.

To carry out the procedure, the image must first be opened in the software, where all points are marked, enclosing an area to form a polygon. Each image may contain one or more polygons. When saving, a JSON file is generated with specific coordinates for the marked regions (Figure 1).

Each object within the array of shapes will describe points, and a description will be provided during marking. Additionally, a reference will indicate which image these points were generated from.

After this step, a structure must be built to iterate through each vector of points, resulting in the complete segmentation of the regions of interest, as shown in Figure 2.

Definition and Calculation of Pigmented Regions

After segmentation, the color space was converted from BGR to HSV to isolate the pigmented regions. The hue (H) component was calculated as presented in Equations 1-3.

Figure 1. File generated after point marking.

```
{
  "version": "5.5.0",
  "shapes": [
    {
      "label": "E_In_C",
      "points": [
        [431.36, 98.98], [399.96, 174.56], [381.36, 273.40]
      ],
      "shape_type": "polygon"
    }
    ...
  ],
  "imagePath": "imgs/PHOTO-2024-05-29.jpg"
}
```

Figure 2. LabelMe segmentation result.

Equations 1-3.

$$H = \begin{cases} 0 & \text{if } \Delta = 0 \\ 60^\circ \times \left(\frac{G-B}{\Delta} \mod 6\right) & \text{if } C_{max} = R \\ 60^\circ \times \left(\frac{B-R}{\Delta} + 2\right) & \text{if } C_{max} = G \\ 60^\circ \times \left(\frac{R-G}{\Delta} + 4\right) & \text{if } C_{max} = B \end{cases} \tag{1}$$

Saturation was calculated as:

$$S = \begin{cases} 0 & \text{if } C_{max} = 0 \\ \frac{\Delta}{C_{max}} & \text{otherwise} \end{cases} \tag{2}$$

The value (V) was obtained as:

$$V = C_{max} \tag{3}$$

Masks in Images

The creation of masks is a widely used technique for segmenting or isolating specific parts of an image based on defined criteria, such as color, intensity, or textural characteristics. A mask is a binary image where pixels corresponding to a region of interest are set to white (value 255), while all other pixels are set to black (value 0). This technique allows subsequent operations to be applied only to the regions of interest, facilitating image processing and analysis.

In this study, we segmented the image based on color intervals corresponding to the regions of interest. Lower and upper thresholds for the color components in the selected color space defined these intervals. The binary mask checks whether each pixel in the original image falls within the defined color intervals. If a pixel is within the interval, it is set to white (255) in the mask; otherwise, it is set to black (0). It is also possible to combine different masks to create an interval filter for a matrix using a technique known as bitwise operation:

$$\text{Final Mask} = \text{Mask}_1 \,\&\, \text{Mask}_2 \,\&\, ... \,\&\, \text{Mask}_n \quad (4)$$

Results

We present the results obtained from the analysis of pigmented tooth images, focusing on calculating the pigmented area. The processing steps described in previously were applied to isolate and quantify the regions of interest, resulting in the calculation of the area affected by the pigment (Figures 3-5).

The analysis began with obtaining the original tooth image, where an enhancement technique was applied to improve the visibility of the pigmented areas. Additionally, many regions had light interference, which affected the results. The pre-processing ensured that the pigmented regions were highlighted, facilitating subsequent segmentation. After enhancement, segmentation was carried out using a binary mask that isolated the teeth from the rest of the image. This segmentation ensured that only the regions of interest—the teeth—were considered for pigment analysis, eliminating noise and background interference.

The pigmented regions were then identified using specific filters in the HSV color space, focusing on the hues associated with the red pigment. The generated mask allowed for precise isolation of the pigmented areas on the teeth. The area of the pigmented regions was calculated by counting the pixels within these areas. In the example presented, the total pigmented area was determined to be 118,570 pixels. This value represents the extent to which the dental surface is affected by applying the bacterial plaque identification product.

This image's characteristics were well-segmented, as there is a clear separation of the tooth regions and coloration. However, since we aimed for accurate prediction, we avoided false negatives. As a result, the color thresholds became more intense, leading to some issues with images with a gradient color. In this image, we notice that the left central incisor has a darker shade that gradually lightens, and the system did not identify this as a pigmented area.

Figure 3. Main results.

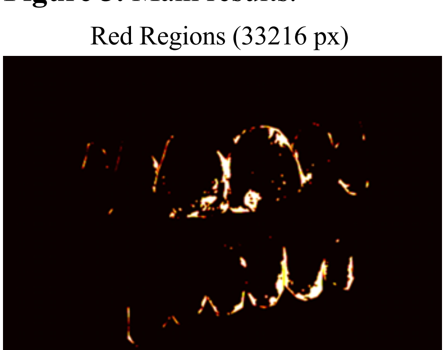
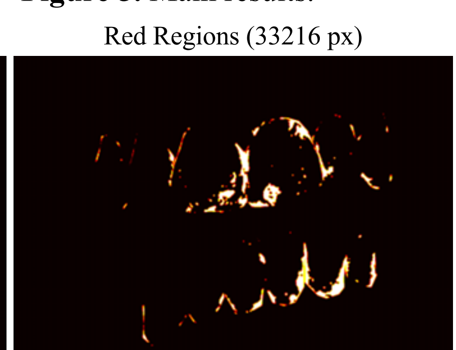


Figure 4. Main results.

Figure 5. Main results.



Since our analysis required fewer false positives, this was an acceptable error, considering that the dyes we aimed to compare mostly exhibited values within more intense intervals. As shown in the following Figures, the image contains regions with isolated dotted areas of pigment, yet the regions of interest were well-segmented, demonstrating the robustness of the method employed for identification.

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