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Detection of Oral and Dental Tissue from the Biomaterials Used in Teeth Using Medical Image Processing Technique

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Abstract: Oral disease is one of the most common causes of death in some countries. Changing habits and diet, not observing oral hygiene, neglecting the importance and health of teeth are the most important causes of oral diseases, these diseases may be specific to the oral cavity or may contribute to the disease in humans as part of an incompatible substance. In the meantime, the field of image processing has been proposed to provide automatic systems for disease diagnosis. Among medical image processing methods, image edging is the process of identifying and changing the display of an image. The purpose of this study is to use the edge recognition method and compare it with previous algorithms to be able to more accurately identify oral tissue from biological materials used in teeth than in the past. In the present study, using the method of Image segmentation (edge detection) is labeled for each pixel, so that pixels with the same label have similar properties. Oral and dental tissue segmentation was performed. Quantitative analysis of the results showed an accuracy of over 80% of the proposed method for oral tissue diagnosis. So that by using the results, it is possible to best identify a person who has a lesion in the tooth or oral tissue.

Keywords: Oral Tissue, Dental Images, Edge Detection, Segmentation, Image Processing

1. Introduction

The oral cavity is the first part of the gastrointestinal tract and at its posterior end has a common path with the respiratory system [1]. The tonsils are on either side of the throat and between two folds of tissue, one at the back and one at the front, which is called tonsillar columns [2]. It is worth mentioning that the pharyngeal region, which is located at the end and behind the oral cavity, is the common pathway between the two gastrointestinal and respiratory systems [3]. In addition, the respiratory tract starts from the nasal cavity and after passing through the nasopharynx, oral pharynx, larynx, tracheal larynx, and bronchi, it ends in the lungs [4]. The oral cavity can be divided into two parts: Between the lips and cheeks with the teeth (in toothless people there is a space between the lips and cheeks) [5]. 2. The true oral cavity: It is a space that is located behind the teeth and continues to the area of the tonsils. Everyone who deals with the oral cavity, such as the dentist, dental assistant, laboratory technician, oral hygienist, should be aware of the natural anatomy of the oral cavity.

1.1. Related Work

Oral disease detection and edge detection are important steps in Biomaterial and cancer diagnosis. The initial proposals for Detection of Oral and Dental Tissue from the Biomaterials in oral images were based on edge detection, image-processing techniques. However, last approaches have some limitations like the number of parameters to be set empirically. For instance, application of the thresholding technique needs that all the nuclei in the images have significant intensity differences against the background and do not produce consistent results if there is considerable variability within the image sets [6]. In recent years, edge detection methods are outperforming the basic approaches in many image segmentation problems [7]. Proposed an efficient and accurate edge detection based method, to the general segmentation problem.

1.2. Biomaterials

Biomaterials have been used in many clinical situations and have interesting results in periodontal reconstruction and bone reconstruction methods. Any research on new implants or related techniques requires basic science research, in vitro and in vivo [8]. For example, understanding and developing platelet-rich leukocyte-rich fibrin (L-PRF) and related biotechnologies, which is one of the growing topics for clinical applications of restorative medicine today, to test, validate, optimize Finally, development for a wide range of applications in other fields requires pharmaceutical, biological, and tissue engineering concepts. Finally, implantable materials are a good example of applied research that correlates to the precise engineering of chemical and morphological properties of materials [9]. Besides, their adaptation to biological behaviors and concepts, their efficacy in the body and humans, and ultimately the understanding of their long-term clinical outcomes and possible diseases. As a result, we are now in the early days of tissue engineering and medicine [10]. Reconstruction and its numerous applications in dental implants we are. Biomaterials and new technologies are the keys to the development of this field, and their development itself requires considerable effort in applied and multidisciplinary research to answer the remaining questions, efficiency, and reproducibility of this pioneering scientific field [11].

1.3. An Overview of Medical Image Processing

Medical imaging is the process used to make images of the human body (or parts and functions thereof) for clinical purposes (medical procedures seeking to identify, treat, and evaluate diseases) or medical sciences (including anatomical and physiological studies) [12]. Medical imaging is an overlap of several disciplines such as medical physics, medical engineering, biology, and optics. Different types of medical radiographic imaging This type of imaging is used to diagnose various types of fractures, dislocations, types of stenosis, and wounds in the gastrointestinal tract, limb tears, joint diseases, etc. CT scans for emergencies such as stasis, shock, and bleeding can be seen quickly. It is also necessary to perform this type of imaging on the spine, chest, and abdomen. Ultrasound is used to check for a variety of diseases related to biliary, urinary, vascular, heart, and pregnant women and children. MRI This type of imaging quickly shows very small buildings and shows the boundary between adjacent tissues well. It also shows muscles, arteries, tendons, and ligaments well [13]. Types of medical imaging devices Simple radiology devices in these devices by producing X-rays in a tube and using a series of necessary techniques and conditions and passing the radiation through the patient's body and its contact with the film and then recording the image by the emergence and fixation devices from different body parts are removed. CT scan machine in this device, cross-sectional and transverse imaging is done by rotating the device around the desired organ, and in each rotation, it captures a section of the organ in the shortest time, and a computer reconstructs the images. An MRI machine uses a large magnetic field that, when the patient is placed in it, the radio waves sent by the device affect the nucleus of the hydrogen atom in the body and place them in a magnetic field. Then the computer imagery is done from different parts of the desired member [14]. To use this system, the PET device injects a radioactive element that produces positrons into the patient's body and then generates two gamma rays. Accordingly, in this system, the anatomy and physiology of the body are determined [15]. The nuclear medicine of a radioactive substance is used intravenously or orally or by inhalation. Due to metabolic functions in the body, these radioactive substances accumulate in a specific place. Then a camera in this system called a gamma camera counts the number of gamma rays emitted by the patient, which indicates the amount of activity absorbed in that organ.

2. Methodology

Segmenting an image refers to splitting the image into regions so that the pixels in each region have a specific feature (which can belong to an object) in common. The most basic feature in segmenting a monochrome image is the brightness of the image and in segmenting a color image, its color components. Besides, the edges of the image and the texture are useful features for segmentation. In this method, we use the image processing technique to identify the oral and dental texture of the biomaterials used.

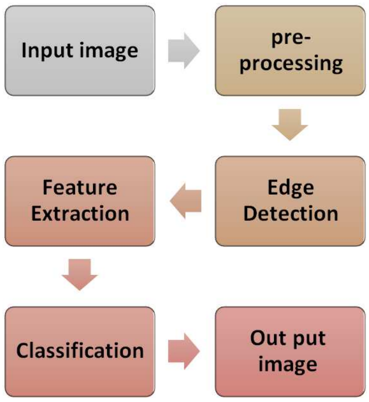


Figure 1. *Oral and dental tissue segmentation diagram.*

Based on the definition of the edge as the location of changes in lighting levels, the range of these changes should also be considered to decide on the presence of the edge and its exact location. In this case, if the edges of an image are exposed, the location of all the prominent and opaque objects in the image is determined and their basic properties such as surface, environment, shape structure, type, and position of objects, only by processing limited points of the image that the edges They will be measurable and recognizable.

$$\nabla f(x,y) = \begin{bmatrix} g_x \\ g_y \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \quad (1)$$

$$|\nabla f(x,y)| = \text{mag}\,\nabla f(x,y) = (g_x^2 + g_y^2)^{\frac{1}{2}} = \left[\left(\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2\right)\right]^{\frac{1}{2}} \quad (2)$$

$$\nabla f = |g_x| + |g_y|$$

$$\theta(x,y) = \tan^{-1}\left[\frac{g_x}{g_y}\right] \quad (3)$$

$$|\nabla f(x,y)| = |f(x,y) - f(x+1,y+1)| + |f(x+1,y) - f(x,y+1)| \quad (4)$$

After preprocessing the input data and linear conversions, the desired image was obtained to perform the correct segmentation. Most images include objects with a uniform brightness level that are on a background with different brightness levels, a binder that can be used to segment an object from the background. (I) brightness, (k) white surface, and (x) gray surface were considered.

$$f(x) = \begin{cases} x, x < I \\ x + k, x \geq I \end{cases} \quad (5)$$

By defining, the threshold for identification and the brightness of the white surface, segmentation was performed (Equation 5). By expanding the brightness and gray level, information extraction was started from inside the image and by labeling each pixel of the image, a distinction was made between white and gray surfaces.

The raw data used were collected separately, in the mentioned method using MATLAB software version 2020a to identify oral tissue in the first stage, the image of human oral tissue as input, with background uniformity and improving image resolution was pre-processed. In the second stage, the identification was performed using the segmentation method. After removing the dental tissue and materials used in the mouth, the candidate points are revealed from the image. In the third and final step, the pixel comparison method was used to extract the final information. Surfaces are important in oral image analysis; the most important features can be extracted from surfaces (including corners, lines). The output of the process is a set of sections whose assembly comprises the whole image or a set of lines extracted from the image. Each pixel in each section is similar in that it has specific properties such as color, brightness, or texture. Adjacent sections are considered different from each other according to the mentioned features.

3. Results

Oral and dental tissue images entered the MATLAB software environment. In this section, after preprocessing (after obtaining image input information, preprocessing operations are performed, which apply methods to eliminate noise and isolate and improve the differentiation of areas where there is a possibility of verbal and numerical information in the image) The segmentation algorithm was performed, a process in which by operating on the data, its salient and defining features are determined. Then, extracting a feature that can describe the image with little information, these features must-have properties so that each unique image can be described with a set of these features (figure 2).

Table 1. *Results obtained from Edge Detection.*

Experiment	Mean Sensitivity (%)	Mean Accuracy (%)
Image 1	90.54	85.25
Image 2	84.65	84.76
Image 3	83.87	86.98
Image 4	92.09	81.75
Image 5	87.98	83.15
Image 6	89.32	89.99
Image 7	88.59	87.76
Image 8	91.75	80.85
Image 9	89.99	82.81
Image 10	86.22	85.98

Table 2. *Result obtained in the statistical measurement.*

Parameter	Accuracy	Sensitivity	Processing time
Segmentation	90	93	3.5
SVM	83	84	4
KNN	86	82	3
Native Bayes	81	79	4.5
Decision Tree	79	76	4

Table 3. *Comparison of segmentation with traditional methods in machine vision.*

Parameter	Segmentation	Traditional methods in machine vision
Accuracy	High	Low
Computing	Complex	Complex
Sensitivity	High	Low
Processing time	Low	High

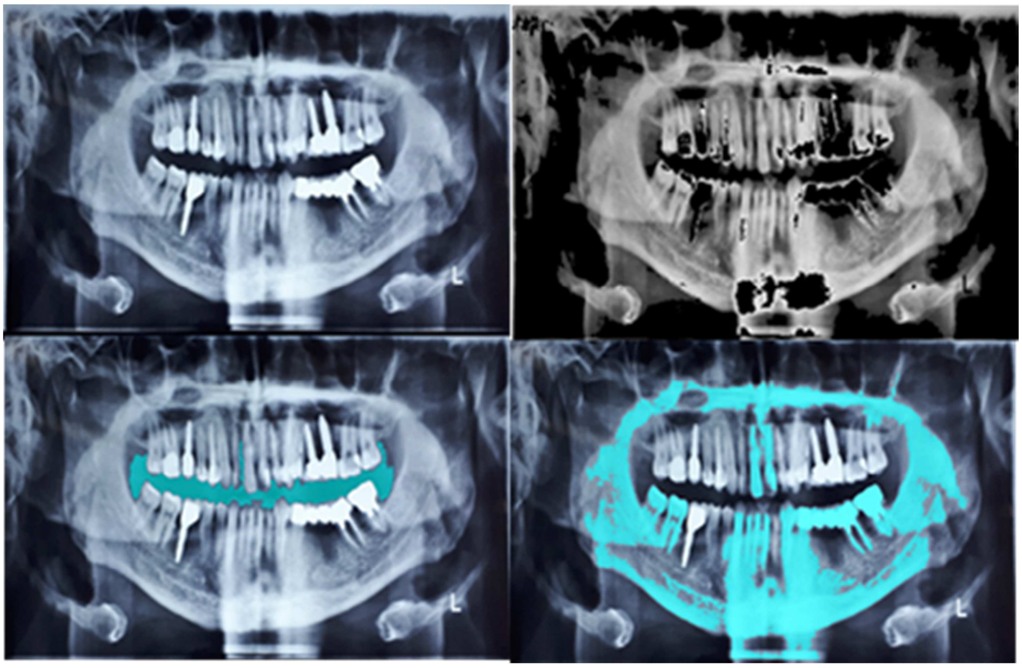
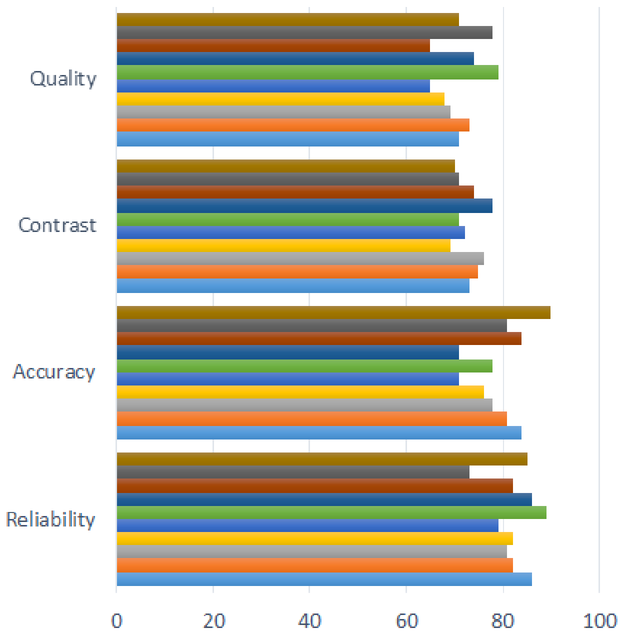


Figure 2. *Results of simulation images.*



	Reliability	Accuracy	Contrast	Quality
Image 10	85	90	70	71
Image 9	73	81	71	78
Image 8	82	84	74	65
Image 7	86	71	78	74
Image 6	89	78	71	79
Image 5	79	71	72	65
Image 4	82	76	69	68
Image 3	81	78	76	69
Image 2	82	81	75	73
Image 1	86	84	73	71

Figure 3. *Results from the accuracy, precision, contrast and reliability of the images.*

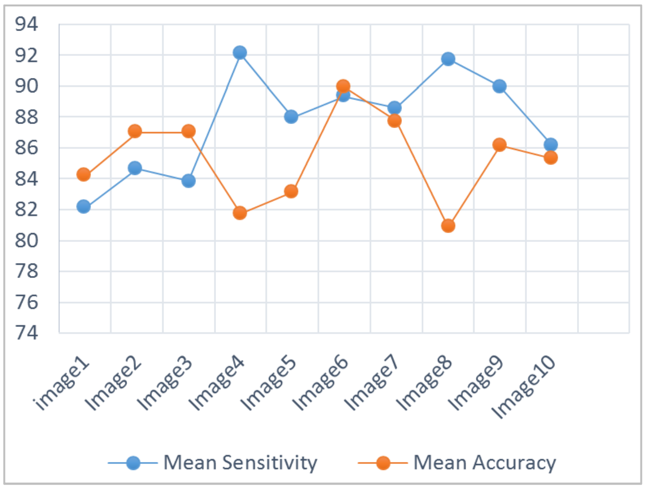


Figure 4. *Edge signal extracted from the image.*

4. Discussion & Conclusion

The traces of image processing can be seen in many sciences and industries, and some of these applications are so dependent on image processing that they fail to achieve their goals without it [16]. Deals with methods that can be used to understand the meaning and content of images. According to the comparison table, it can be concluded that the segmentation method is much more accurate than traditional machine vision methods [17]. The image was divided using a series of decisions and the desired result was obtained, which allows the physician to make a correct diagnosis and extract the information with high accuracy [18]. The purpose of segmenting an image is to make the raw data more usable for later statistical processing. It is expected that in the future, feature extraction will be done more accurately and more details will be provided to the machine's visual systems to identify the objects in the image, which will speed up the diagnosis of the disease. The method of segmentation based on mathematical tools is an efficient method for processing Oral images and thus improving image accuracy. Using special features, it is possible to focus on time, scale, and maintain important coefficients (information) for analysis. The resolution and contrast of Oral images are almost unaffected by the segmentation method [19]. Considering the images and relative values of accuracy, precision, and speed of data processing, among all the mentioned methods, the best case is when the segmentation method is used [20]. In this case, the fragmented image has the highest accuracy. Research into the use of a large number of low-quality cameras to match images and compare their performance with systems that use two high-quality cameras is one area of research that can be explored. Very little research has been done on displaying 3D pixel-based memory of scenes and storing important features in scenes such as corners and edges. Besides, as more and more researchers turn to graphic processing units to perform processes related to machine vision (two-way matching, scene reconstruction, and object recognition), it is expected that the position of the three-dimensional pixels will be determined more accurately and in detail. More to be provided to image processing systems to identify objects in the image [21]. The database employed in this study has a limitation of images and in future works, the number of images will be expanded and images of human dysplastic oral tissues will be employed.

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