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# Osteoradionecrosis Region Estimation Using Machine Learning

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**Abstract:** Osteoradionecrosis is a disease caused by a bone resorption inhibitor or the radiation therapy to the head and neck cancer. Conservative therapy using antibacterial drug or surgery to remove the necrosis bone have been done in the ORN treatment. Currently, the surgical operation often takes longer time than the pre-operative surgical plan, because it is difficult to recognize the bone necrosis area in the 3D CT image. Therefore, a system to accurately estimates the osteoradionecrosis area in the pre-operative 3D CT image is needed. This paper proposes a method to estimate the osteoradionecrosis area using image texture features and machine learning. Experiments using two osteonecrosis patients CT images showed that the necrosis area was successfully extracted by the F-measure score of 0.729, and we confirmed the necrosis area estimation result through the visual inspection.

**Keywords:** Osteoradionecrosis, Computed tomography, Machine learning, Texture analysis, Segmentation

## 1. INTRODUCTION

Osteoradionecrosis (ORN) is a disease caused by a bone resorption inhibitor or the radiation therapy to the head and neck cancer. Conservative therapy using antibacterial drug or surgery to remove the necrosis bone have been done in the ORN treatment. Hayashida *et.al.* reported that the surgical treatment is more effective to cure the ORN in a short period of time[1]. In the surgery, oral surgeons remove the necrosis bone based on the pre-operative surgical plan made by radiologists and oral surgeons. Currently, the surgical operation often takes longer time than the expected surgical time because size of necrosis area is incorrectly recognized in the surgical planning.

As the related works, Ref.[2] proposes the method to detect the bone infection in diabetic foot magnetic resonance image (MRI) using machine learning. Ref.[3] proposes a method to detect necrosis area in pathological image using texture features. These methods focus on the detection of necrosis caused by a disease, but there was no method to extract the necrosis area in the head computed tomography (CT) image.

This paper proposes a method to automatically estimate the ORN region in the pre-operative head CT image. The proposed method calculates the texture features based on the gray level co-occurrence matrix (GLCM). A machine learning based two class classifier is trained to distinguish the ORN image feature from the feature extracted non-ORN region.

This paper organized as follows. Section2 describes subjects and materials used in this study. Section3 proposes a method to estimate the ORN region in the subject's 3D head CT image. Section4 performs experiments to reveal the best machine learning method in the ORN region estimation task, and applies the proposed method to a CT image slice to visually evaluates the performance. Finally, section5 concludes this paper with future works.

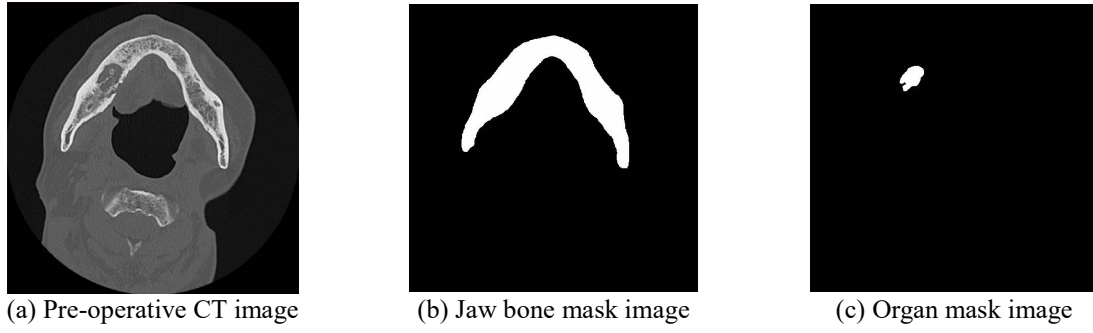
## 2. SUBJECTS AND MATERIALS

This paper employs two ORN subjects whose pre-operative head CT image and post-operative specimen CT image were acquired in the Kobe University Hospital. We had obtained informed consent from all subjects.

The pre-operative axial 3D CT images have  $512 \times 512 \times 451$  or  $225$  voxels and image spacing is  $0.351 \times 0.351 \times 0.3$  mm. Figure 1 shows the pre-operative CT image, jaw bone mask image and organ mask image. The jaw bone and organ mask were manually drawn and were confirmed by two well trained oral surgeons.

## 3. PROPOSED METHOD

According to the progression of osteoradionecrosis, the density of trabecular bone in the cancellous bone is reduced because the osteoradionecrosis damages the trabecular structure. The trabecular bone has mesh shape



**Figure 1:** Example of subject image.

in the CT image, therefore, the proposed method estimates the osteoradionecrosis region using texture feature and machine learning.

### 3.1 Feature extraction

In order to calculate the image texture feature, this study extracts some  $10 \times 10$  pixels image patches from a CT slice. This study employs GLCM to evaluate the trabecular structure in the extracted small image patch image as a texture feature. The raw CT value may take negative value, therefore, this study normalizes the CT value by the following equation.

$$\mathbf{X}_p = \mathbf{X}_0 - \min(\mathbf{X}_0) \quad (1)$$

where  $\mathbf{X}_p$  is the CT image without negative CT values,  $\mathbf{X}_0$  is the original CT image, and  $\min(x)$  calculates the minimum value in the given matrix  $x$ .

Raw CT value takes very large range, therefore, the GLCM calculation requires very high computational cost. The minimum CT value in the image  $\mathbf{X}_p$  is already converted to 0, we converts the CT value ranges between 0 and 100 by;

$$\mathbf{X} = \frac{\mathbf{X}_p}{\max(\mathbf{X}_p)} \quad (2)$$

where  $\mathbf{X}$  is the normalized CT image, and  $\max(x)$  calculates the maximum value in the given matrix  $x$ .

Finally, we calculate the GLCM from the image patch in the normalized CT image. We calculate three texture properties (contrast, correlation and homogeneity) from GLCM  $\mathbf{p}$  by the following equations.

$$Contrast = \sum_{i,j} |i - j|^2 \mathbf{p}(i,j) \quad (3)$$

$$Correlation = \sum_{i,j} \frac{(i - \mu)(j - \mu)\mathbf{p}(i,j)}{\sigma^2} \quad (4)$$

$$Homogeneity = \sum_{i,j} \frac{\mathbf{p}(i,j)}{1 + |i - j|} \quad (5)$$

where  $i$  and  $j$  are horizontal and vertical index in the GLCM  $\mathbf{p}$ ,  $\mu$  is average of GLCM elements, and  $\sigma$  is the

variance of GLCM elements.

### 3.2 Osteoradionecrosis region estimation

The proposed method employs machine learning to estimate the existence of osteoradionecrosis from the texture properties calculated from an image patch. The proposed method performs the two class classification to distinguish the image patch including osteoradionecrosis region from healthy bone patch.

The following equation standardizes the extracted texture features to the average of 0 and standard deviation of 1 for the efficient training of classifier.

$$\mathbf{X}_n = \frac{\mathbf{X} - \mu_t}{\sigma_t} \quad (6)$$

where  $\mu_t$  and  $\sigma_t$  are element wise average and standard deviation in a subject.

## 4. EXPERIMENTAL RESULTS

### 4.1 Dataset

We extract image patches from CT slices using sliding window method with sliding step width of 5 pixels to overcome the limitation of the number of subjects. Because the size of osteoradionecrosis organ is small in comparison to the whole CT image size, the image region to apply the sliding window method must be limited. A simple thresholding method can easily extract bone region from CT image, this paper extracts image patches from the jaw bone region.

In the experiment, an image patch whose 80% or more

**Table 1:** Number of image patches used in the experiment. The normal and the abnormal show the healthy and osteoradionecrosis, respectively.

	Normal	Abnormal	Total
Subject #1	1,620	405	2,025
Subject #2	1,620	1,323	2,943

**Table 2:** The confusion matrix of Random Forest based estimation result.

		Estimation result	
		Abnormal	Normal
Ground	Abnormal	0.333	0.667
Truth	Normal	0.027	0.972

**Table 3:** The confusion matrix of Neural Network based estimation result.

		Estimation result	
		Abnormal	Normal
Ground	Abnormal	0.540	0.460
Truth	Normal	0.062	0.937

**Table 4:** The confusion matrix of Support Vector Machine based estimation result.

		Estimation result	
		Abnormal	Normal
Ground	Abnormal	0.603	0.397
Truth	Normal	0.051	0.949

pixels are annotated as osteoradionecrosis organ as the ORN image patch. Table 1 shows the number of image patches extracted as normal (healthy bone) region and abnormal (osteoradionecrosis bone) region.

#### 4.2 Comparison of machine learning algorithms

We compare the osteoradionecrosis region estimation accuracy using three machine learning algorithms: Random Forest (RF), Neural Network (NN), Support Vector Machine (SVM). Following experiments uses randomly sampled 70% of image patches in the training, and resting image patches are used only in the evaluation.

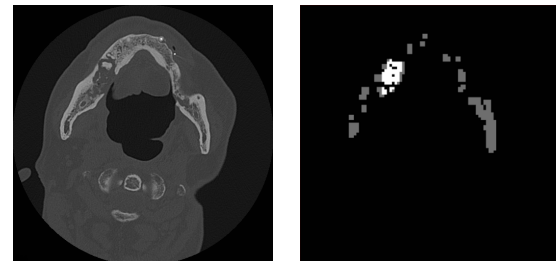
Table 2, Table 3 and Table 4 show resulting confusion matrix using three machine learning algorithms. The precision, recall and F-measure for each result is calculated as shown in Table 5. The RF and SVM results have similar precision value, but the most of region were estimated as non-osteoradionecrosis (normal) region in RF result. The SVM result has highest score in recall and f-measure, therefore, the SVM is most suitable classifier for the osteoradionecrosis region estimation.

#### 4.3 Visualization of osteoradionecrosis region estimation

We performed the slice-by-slice osteoradionecrosis

**Table 5:** Comparison of osteoradionecrosis region estimation performance.

	Precision	Recall	F-measure
RF	<b>0.925</b>	0.333	0.490
NN	0.897	0.540	0.674
SVM	0.922	<b>0.603</b>	<b>0.729</b>



(a) Evaluated CT slice (b) Estimation result

**Figure 2:** Osteoradionecrosis region estimation in a CT slice. In the estimation result, white and gray colored region were correctly and incorrectly estimated as the osteoradionecrosis region, respectively.

estimation to visualize its result. In this experiment, image patches included in the evaluating CT slice are excluded from the dataset to train the classifier, and we employed SVM which achieved highest f-measure score in machine learning algorithm comparison. The evaluated raw CT image slice and estimation result are shown in Figure 2(a) and (b). In the estimation result, the black region shows the non-bone region that was not evaluated in the estimation and the region estimated as healthy bone. The white and the gray colored region were correctly and incorrectly estimated as the osteoradionecrosis region, respectively. We visually confirmed that the most of osteoradionecrosis region is estimated correctly but many parts of healthy bone were estimated as osteoradionecrosis as the high precision score and low recall score in Table 5 also described.

## 5. CONCLUSION

This paper proposed the osteoradionecrosis region estimation method using machine learning and image texture feature extracted from CT images. The experimental results using two subjects showed that the SVM produced the highest estimation accuracy in f-measure score (0.729). Through the visual inspection, we confirmed that the osteoradionecrosis region was successfully estimated but many parts of healthy bone were estimated as organ.

In the future, we will improve the estimation accuracy by reducing the recall score. In order to improve the estimation accuracy, we will increase the number of training dataset by three dimensionally extracting the image features from pre-operative CT images. Moreover, we will extract the image features using convolutional neural networks.

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