# Automatic extraction and visualization of coronary artery calcium using optical frequency domain imaging

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**Abstract:** Imaging of coronary artery calcification using optical coherence tomography (OFDI) is an essential task in cardiac catheterization. Recently, many studies have been conducted to detect lesions from OFDI images, and diagnostic support systems equipped with these tools have been developed. However, the interfaces of existing diagnostic support systems pose difficulties in assessing thin areas of calcification, which are important for determining the presence of diastolic dysfunction. In this study, we created a deep learning neural network model that automatically extracts calcified areas from OFDI image of coronary artery. For the extracted calcified areas, to display the thickness of calcification more intuitively, we expressed the continuity as a ring shape and the thickness as color information.

**Keywords:** Deep Learning, OFDI image, Semantic Segmentation, Visualization.

## 1. INTRODUCTION

Optical frequency domain imaging (OFDI) is now widely used in the catheterization and treatment of coronary arteries. OFDI is an intravascular diagnostic imaging system with a high resolution of 10-20μm, based on near-infrared laser light and fiber-optic technology. It can evaluate calcification with a spatial resolution ten times higher than intravascular ultrasound (IVUS), and it can extract calcification clearly with high resolution, so it has been introduced in various facilities.

Recently, machine learning models to detect and classify lesions from OCT images have been reported in [1, 2, 3]. In particular, Chu et al. developed a new AI framework that can automatically characterize plaques pixel by pixel, and integrated it into a commercial diagnostic support system (Fig. 1) to achieve a highly accurate classification display of lesions in vascular cross-sections [3].

In addition, Abbott, located in the U.S., developed Ultreon 1.0, an AI-based software package for cardiovascular OCT diagnostic imaging systems. Fig. 2 shows the user interface. It displays calcified areas by drawing arcs around the cross-sectional view of blood vessels [4]. However, although these interfaces provide an evaluation of the continuity of the calcified area, only the maximum thickness of the calcified area is displayed, and no other thickness evaluation is available.

Since the information required in percutaneous coronary intervention (PCI) is not the maximum thickness but whether there are regions with a thickness less than 0.5 mm, this paper proposes a visualization method, the output of which can be understood more intuitively according to the continuity and thickness information for calcified regions. Specifically, the continuity information is represented as a ring shape, and the thickness information is represented as color information simultaneously.
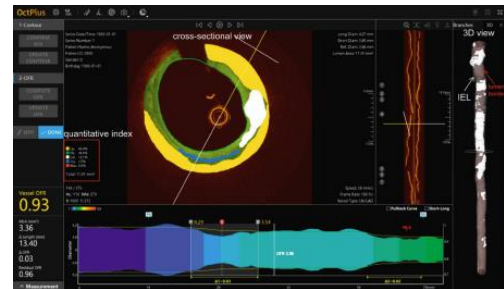


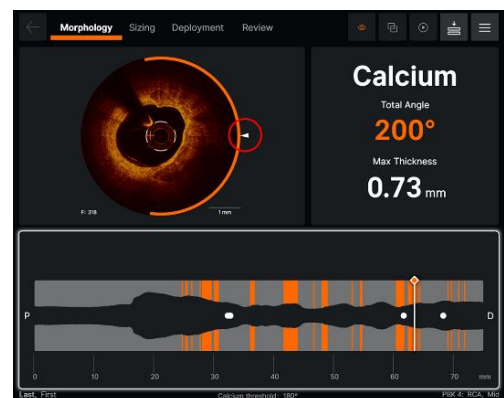Fig. 1 Visualization of lesion with OctPlus software.



Fig. 2 Visualization of calcified area with Ultreon 1.0

## 2. METHOD

In this method, deep learning is used to extract the calcified regions [5]. The dataset consists of 2,149 coronary OCT images labeled by a physician. For labeling, the physician traces the inner boundary in red and the outer boundary in yellow, and two experts cross-check the results. Each line segment constitutes a closed boundary, and the calcified area is automatically filled from this boundary (Fig. 3). The

training data is subjected to a flip and a rotation (eight different rotations in 45-degree increments), and finally, the original data is data-enhanced by a factor of 16 (Fig. 4). The training is performed using DeepLabv3+, a network for semantic segmentation.
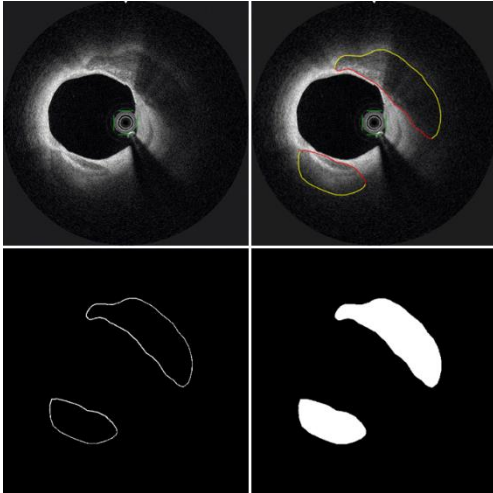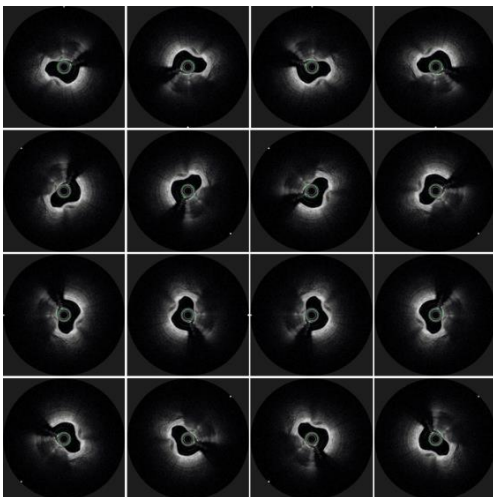


Fig. 3 Creating a labeled image.



Fig. 4 Data augmentation.

In order to visualize the extracted calcified area, it is necessary to remove artifacts such as catheters, guidewires, and crosshairs drawn by the DICOM viewer. First, the catheter is displayed in the center of the OFDI image because the catheter is shifted along the guidewire inserted into the blood vessel in OFDI (Fig. 5A). After binarization using Otsu thresholding method (Fig. 5B), pixels in the catheter area are removed (Fig. 5C). A median filter is used to remove the guidewire (crescent-shaped signal on the side of the catheter) and the crosshairs drawn by the DICOM viewer (Fig. 5D).

Since the guidewire reflects light strongly, a shadow is created in the region behind it. Since it is desirable to detect this shadow and exclude it from the calculation, the region is detected by scanning the pixels radially from the center of the image to the periphery (Fig. 5E). Next, it is necessary to calculate the thickness of calcification by using the lumen

center of the vessel instead of the image center. Since the luminal center is equal to the center of gravity of the luminal region, we construct a closed boundary for the vessel wall by connecting the non-zero pixels detected in the scanning described above, and find the center of gravity of the figure filled inside the boundary (Fig. 5F). Using these data, we visualize the extracted calcified area.
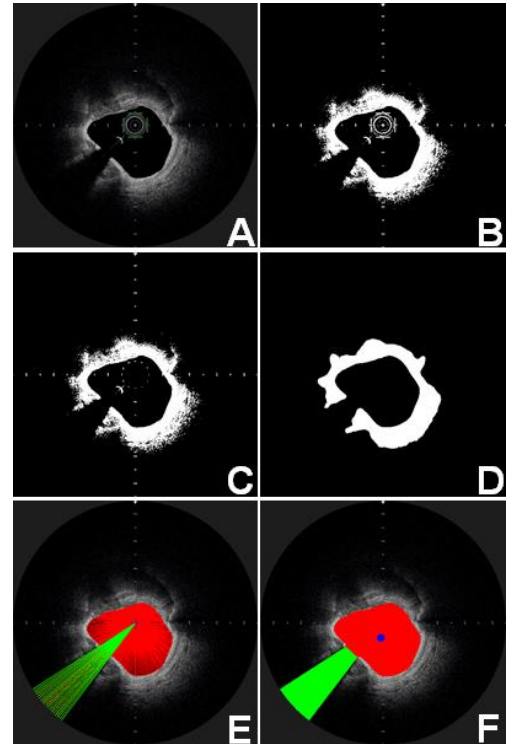


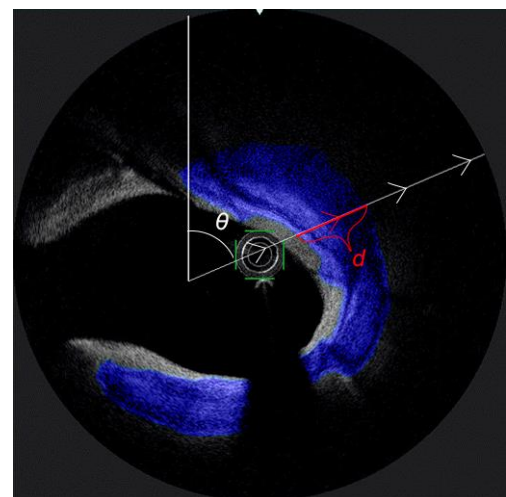Fig. 5 Detection of guidewire shadow and lumen center.



Fig. 6 Calculating the thickness of calcification as a function of the angle.

At first, the thickness of the calcification is calculated radially, at certain angles, using the center of the vessel lumen as the origin, and the maximum value of the angle and thickness of the region where the calcification is continuous is obtained (Fig. 6). Based on the results in Fig. 5F, the area that is shadowed by the guidewire is excluded from the

calculation. The thickness, $d(\theta)$, is the thickness of the calcified area from the center of the vessel lumen at an angle $\theta$ and is defined by Eq. (1):

$$d(\theta) = \alpha \sum_{r=0}^{L} S(P) \qquad (1)$$

$$S(P) = \begin{cases} 1 \ if \ P(rcos\theta, rsin\theta) \ is \ calcified \\ 0 \ if \ P(rcos\theta, rsin\theta) \ is \ not \ calcified \end{cases} \qquad (2)$$

Here, $P$ is the pixel position, $r$ is the distance from the origin, $\theta$ is the angle shown in Fig. 6, and $S(P)$ is a function that returns calcification (1) or non-calcification (0). $\alpha$ is an adjustment from image space to distance and is calculated from pixel length and image size.

The method displays a circle colored according to the thickness of the calcified area. The color space is calculated using the HSV color system (Fig. 7), and finally is converted to the RGB color system. $H$ represents the hue, which is calculated using equation (3).

$$H = H_{max} * (1 - (d(\theta)/d_{max})), \qquad (3)$$
$$0 \leq H$$

The constant $H_{max}$, which represents the maximum value of $H$, is set to 240 (blue). The constant $d$, which represents the maximum thickness of the calcified area, is set to 0 (red) for $d(\theta) > d_{max}$.
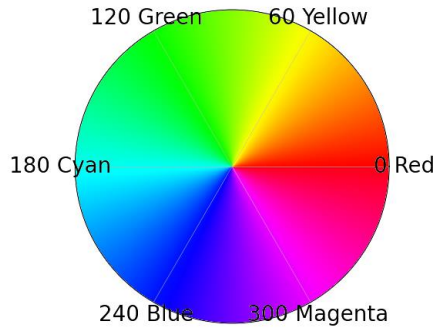


Fig. 7 Hue rings used for calculations.

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**Algorithm 1** Algorithm for Color

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1: $H = H_{max} * (1 - (d(\theta)/d_{max}))$
2: **if** ($H < 0$) **then**
3:    $H = 0$
4: **end if**
5: $C$ = hsv_to_rgb(h, 255, 255)

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Fig. 8 Algorithm for color calculation.

The overall algorithm is described in Fig. 8. The RGB color for a thickness $d(\theta)$ is defined by C, and hsv_to_rgb is a function to convert the color space from HSV to RGB.

The final visualization results from the obtained data are shown in Fig. 9. The threshold value, $d_{max}$, is set to 1.0. Areas with no calcification are marked in blue, and areas

with significant calcification are marked in red. Max Angle is the maximum angle at which calcification is continuous, and Max Thickness is the maximum value of the thickness.
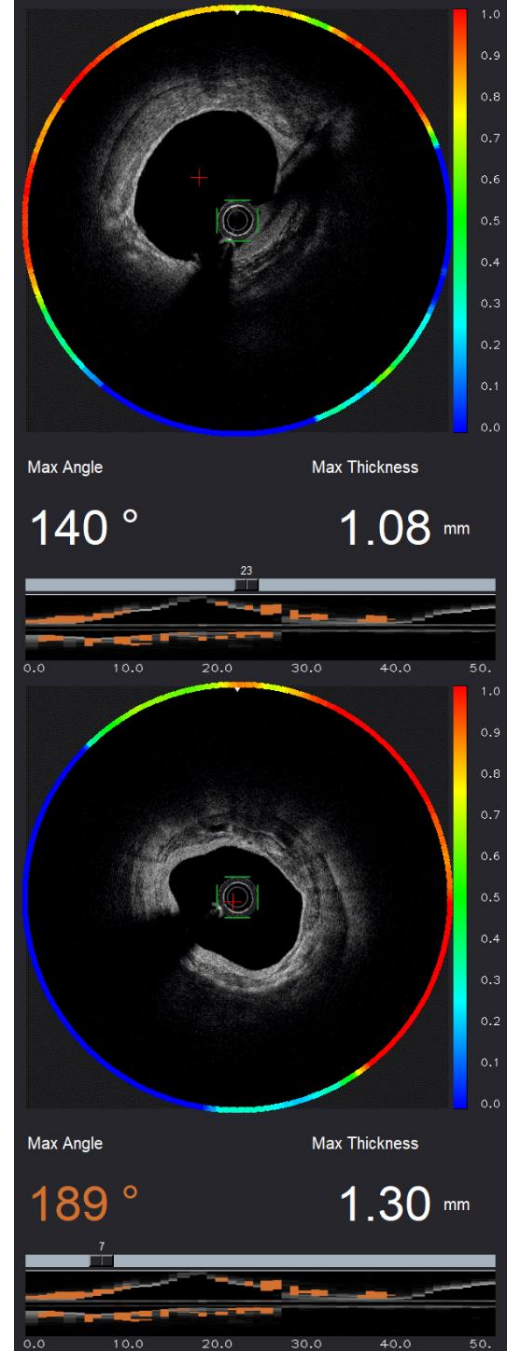


Fig. 9 Visualization of calcified area.

## 3. DISCUSSION

As opposed to the existing commercial software package Ultreon (Fig. 2), the proposed method displays colored circles according to the thickness of the calcified area. We believe that the proposed method enables us to visualize the continuity and thickness of calcified areas, which are important for diagnosis, in a more intuitive manner. In particular, the proposed system would be useful for predicting dilation, because it was difficult to evaluate thin

areas of calcification with Ultreon, where calcified areas are likely to be cracked by balloons. The verification results for the model used in the experiments are shown in Fig. 10. The validation environment is shown in Table 1. The dark blue part of the image shows the calcified area, and the light blue part shows the non-calcified area. The accuracy and Intersection over Union (IoU) are shown in Table 2.

Table 1 Validation environment.

| CPU | Intel® Core™ i9-9940X |
|---|---|
| RAM | 128GB (16GB×8) |
| GPU | NVIDIA QUADRO RTX 8000 ×4 |
| OS | Ubuntu 18.04 LTS |
| Patients | 44 |
| Image size | 512 × 512 pixels |
| Training data | 31,184 |
| Test data | 200 |
| Epochs | 500 |
| Minibatch size | 32 |
| Initial learning rate | 0.0001 |
| Optimizer | Adam |

Table 2 Accuracy and IoU

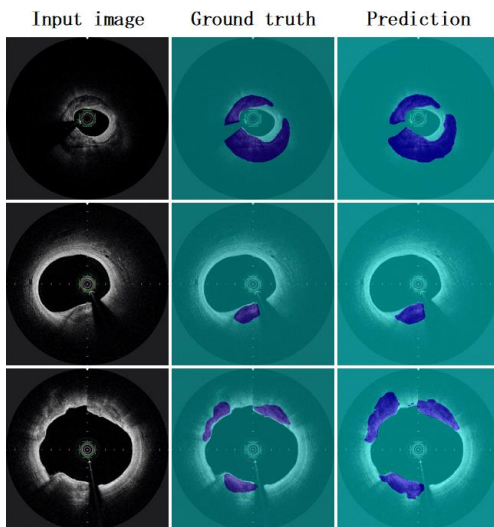| | Calcium | Background |
|---|---|---|
| Accuracy | 0.81 | 0.98 |
| IoU | 0.62 | 0.97 |



Fig. 10 External validation results.

## 4. CONCLUSION

In this paper, we proposed a method to visualize calcification images extracted from coronary artery OCT images in a more intuitive manner. The continuity of the calcified area is represented as a ring shape, and the thickness information is represented as color information, which enables physicians to understand the calcified area intuitively. At present, it is possible that the calcified area, which is discontinuous due to the shadow of the guidewire, is actually continuous, but the problem is that it cannot be detected. There is an approach using a generative adversarial network (GAN) to supplement the missing images, and there is room for further investigation of this approach [6].

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