The CNN-based Coronary Occlusion Site Localization with Effective Preprocessing Method

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The coronary artery occlusion (CAO) acutely comes to human, and it highly threatens the human’s life. When CAO detected, percutaneous coronary intervention (PCI) should be conducted timely. Before PCI, localizing the CAO is needed firstly, because the heart is covered with various arteries. We handle the three kinds of CAO in this paper and our purpose is not only localization of CAO but also improving the localizing performance via preprocessing method. We improve the area under the receiver operating characteristics curve at CAO site localization from a minimum of 0.150 to a maximum of 0.372 via our noise reduction and pulse extraction-based method. © 2020 Institute of Electrical Engineers of Japan. Published by Wiley Periodicals LLC.

Keywords: coronary artery occlusion; localization; preprocessing method

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1. Introduction

The coronary artery occlusion (CAO) makes thrombus or embolism and these cause sudden blood flow shutting down [1]. The physician will conduct percutaneous coronary intervention (PCI) when the patient is suffering from CAO. However, the heart is covered with various arteries such as left anterior descending artery (LAD), left circumflex artery (LCX), and right coronary artery (RCA) [2]. Also, those arteries show various characteristic with CAO in ECG [3].

For conducting PCI, the physician needs to know the occlusion site of the coronary artery. Taking a CT scan may be more helpful for distinguishing the location, but there is not enough time for CT scan in an emergency situation. On the other hand, ECG can quickly measure the patient’s condition, although only limited information is provided. Thus, we make the best use of ECG for localizing coronary occlusion site.

2. Related Work

One of the studies already shows the high performance at detecting coronary site location using decision tree [4]. They deal with classifying LAD, LCX, and RCA, and their average sensitivity and specificity are 72 and 92.5%, respectively, using improved classification algorithm than their previous work [5]. Sensitivity is a more important indicator than specificity, especially in emergency medicine. However, their sensitivity is 20.5% lower than specificity. This means that only 7.5% of normal patients are missed but CAO patients are missed 28%.

The method for finding patients as much as possible is needed, and accordingly, various studies are already conducted. One of the studies suggests a preprocessing method for better performance in the same classifier [6]. That preprocessing method is dealt with in this research and several experiments for comparing and finding the better method.

3. Proposed Approach

In this section, we present our approach for localizing coronary occlusion site. We refer to the preprocessing method in the previous STEMI detection study [6], and classification algorithm from study of Richard et al. [4]. The above algorithm has not only simplified architecture but also improved performance than their previous work for achieving the same purpose [5]. The preprocessing method is constructed with noise reduction and pulse extraction. The noise reduction is conducted via notch filter and high-pass filter. We apply the above preprocessing method before entering the data to the classifier.

We construct the neural network architectures as shown in Fig. 1 based on ResNet [7]. We construct two CNN architecture using 1D convolution and 2D convolution separately. For comparing the performance, we use two kinds of convolution, one dimensional (1D) convolution, and two dimensional (2D) convolution. We use both architecture for experiment and then we will select more effective model.

Then, we construct the CAO localization classification algorithm based on previous work [4]. They used the three decision trees as a classifier. The first classifier is used for categorizing LAD or not, and the next two classifiers are used to classifying

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proportional and not-proportional LAD and LCX or RCA, respectively. However, we do not have the detailed label as proximal or non-proximal LAD, so we construct the classification algorithm as shown in Fig. 2.

Each stage of Fig. 2 is constructed with CNN as shown in Fig. 1. We pursue to confirming the effectiveness of our preprocessing method based on denoising and pulse extraction at the above classification algorithm in this paper.

The input and output is same as Fig. 1.

Fig. 2. The CAO classification algorithm that constructed with two-stage. We name the classifier that classifies LAD or non-LAD as stage-1 and the other, for classifying LCX or RCA, as stage-2.

In this section, we present our dataset that originally provided by Seoul National University Bundang Hospital, and the experimental results. First, we apply the preprocessing method as used in related work that method contains noise reduction and pulse extraction [6]. We call the each dataset as same as previous work. The two dataset, Set-R and Set-BP that as shown in Table I, are used for experiments. The Set-R contains raw 12-lead ECG records, and the Set-BP contains extracted pulse after applying both high-pass and notch filter. Then, we conduct the experiments using above dataset and the classifier as shown in Fig. 2.

We use the accuracy, sensitivity, specificity, and area under the receiver operating characteristics curve (AUROC) [8] as the performance indicator. The performance measurement is conducted for each of the two stages as the classifier consisted of two stages. The measured performances for each stage are summarized as Tables II and III.

When using the Set-BP, dataset after preprocessing, the performance is highly improved than the case of using raw ECG record, Set-R, both in the 1D-CNN and 2D CNN cases. The AUROC is increased 0.372 and 0.355 for 1D-CNN and 2D-CNN respectively. Moreover, it can be confirmed that the performance of 1D CNN is higher than 2D CNN.

In stage-2, the performance is also improved with Set-BP set. Thus, we confirm that our preprocessing technique can help to improve the CAO classification ability. However, the above two tables show that the 1D-CNN shows better performance than 2D-CNN, so if anyone wants to use CNN for classifying CAO the 1D-CNN is recommended.

### 5. Conclusion

We do not conduct the experiment for finding the optimal structure of the CNN and the hyperparameters for CNN. However, our experiments show that our preprocessing technique, based on both noise reduction and pulse extraction, can improve the classification performance with simple CNN. The performance is improved as much as 0.372 and 0.150 in stage-1 and stage-2 respectively with 1D-CNN. The CAO classification performance will be highly improved if the optimal CNN structure is found with fine hyperparameter. However, when using our preprocessing method, everyone can achieve high performance without finding the fine classifier.

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**Table I. The ECG records are originally provided by SNUBH and it named Set-R. The preprocessed dataset is named as Set-BP**

| Set   | LAD | LCX | RCA |
|-------|-----|-----|-----|
| Set-R | 419 | 70  | 283 |
| Set-BP| 4487| 715 | 2591|

**Table II. Performance of stage-1**

| CNN   | Set  | Accuracy | Sensitivity | Specificity | AUROC  |
|-------|------|----------|-------------|-------------|--------|
| 1D-CNN| Set-R| 0.549±0.039| 0.453±0.072| 0.631±0.064| 0.560±0.046|
|       | Set-BP| 0.910±0.020| 0.895±0.032| 0.921±0.024| 0.932±0.021|
| 2D-CNN| Set-R| 0.569±0.032| 0.450±0.168| 0.658±0.124| 0.571±0.042|
|       | Set-BP| 0.915±0.020| 0.898±0.029| 0.927±0.027| 0.926±0.020|

**Table III. Performance of stage-2**

| CNN   | Set  | Accuracy | Sensitivity | Specificity | AUROC  |
|-------|------|----------|-------------|-------------|--------|
| 1D-CNN| Set-R| 0.70±0.034| 0.944±0.037| 0.062±0.058| 0.513±0.082|
|       | Set-BP| 0.775±0.030| 0.898±0.028| 0.319±0.103| 0.663±0.050|
| 2D-CNN| Set-R| 0.715±0.044| 0.854±0.059| 0.150±0.075| 0.518±0.058|
|       | Set-BP| 0.764±0.038| 0.892±0.050| 0.284±0.117| 0.612±0.062|

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