

# Meta-learning Based Obstructive Sleep Apnea Detection Using Single-Lead ECG Signals

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**Abstract**—As a respiratory syndrome correlated with some cardiovascular diseases, obstructive sleep apnea (OSA) not only destroys the quality of our sleep, but also induces a variety of major chronic diseases such as heart disease, and diabetes, and even causes sudden death during sleep. Many studies have been conducted on the classification of OSA from normal events by machine learning. However, we found that differences in patients caused by the individuality of the ECG patterns and variability in the ECG do not create optimal rules for OSA classification by ECG signals. It is necessary to reduce the impact of individual differences in classification. In this study, we propose a method based on meta-learning to detect OSA using a 2D time-frequency scalogram that is converted from a single-lead ECG signal. According to the experiment results, we achieved 68.10% accuracy, 69.19% sensitivity, 67.71% specificity, and a 0.694 F1 score. The results showed this method based on meta-learning using the Siamese network is feasible without being pre-trained by massive 2D scalogram representations.

**Index Terms**—Electrocardiogram, Obstructive sleep apnea, Medical diagnoses, Siamese network

## I. INTRODUCTION

Obstructive sleep apnea (OSA) arises due to the total (apnea) or partial (hypopnea) repeated interruption of breathing during sleep and induces a variety of major chronic diseases. With the maturity of machine learning technology, more and more researchers are using machine learning to detect OSA from normal. We found that the classification of ECG signals is a challenging problem due to individual differences in patients caused by the individuality of the ECG patterns and variability in ECG waveforms by patients. This issue has no existence of optimal classification rules for ECG classification [1, 2]. Developing the most appropriate classifier that is capable of classifying OSA more accurately by reducing the impact of individual differences is a challenge in OSA classification.

In the context of machine learning, meta-learning can be defined simply as having the ability to acquire knowledge. In the past, the biggest difference between humans and machine

learning systems was that machine learning systems excelled at mastering a single skill, while humans could act intelligently and adapt to a variety of new situations. But the advent of meta-learning has allowed machine learning systems to master similar abilities as humans to adapt to new skills, and Make it applicable to a variety of different learning problems, including classification, regression, and reinforcement learning. The goal of meta-learning is to train a model on a variety of learning tasks, such that it can solve new learning tasks using only a small number of training samples [3].

Although there is a need to eliminate individual differences between patients, this does not imply that the entire training process must utilize samples from only one patient. We introduced the Siamese network [4], a widely used metric-based meta-learning model to be pre-trained by other image-based databases to learn the ability to calculate the distance between different inputs from the extracted features. In this study, we proposed a method to detect OSA by meta-learning using a 2D characteristics scalogram which was converted from a single-lead ECG signal to reduce the influence of individual differences in OSA detection. The performance showed this method is feasible to detect OSA from normal while reducing individual differences.

## II. RELATED WORK

A range of methods for OSA detection using different bio-signals have been proposed. Patients with sleep disorders typically experience cyclic changes in heart rate, which are reflected in ECG amplitude or shape. The R-R intervals, or the interval between heartbeats, can be calculated using ECG signals. Sharma and Sharma introduced a radial basis function (RBF) kernel least-square support vector machine (LS-SVM) for OSA detection based on characteristics acquired from RR intervals using the hermit basic function [5].

With the widespread use of machine learning in the field of sleep medicine. Researchers are starting to use machine learning technologies to distinguish OSA from normal. A number of automatic or semi-automatic detection techniques have been published, including decision trees [6], random forests (RF) [7], SVM [8], multi-layer perceptrons (MLP) [9], and K-nearest neighbors (KNN) [10].

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Unlike traditional machine learning techniques, a convolutional neural network (CNN) can automatically extract features through hierarchical layers without requiring manual extracting features. Wang et al applied a LeNet-5-based approach to classifying OSA from normal. Additionally, many fusion models using CNN have been created. example, Shoeb and Sridhar [11] used a fusion model of CNN and Long Short-Term Memory (LSTM) to extract hidden temporal features in ECG signals. However, the volume of sleep data and characters makes concurrent LSTM training impossible, it will result in low efficiency.

We found that none of these studies considered the individual differences between patients. In order to eliminate the impact of individual differences, we employ the meta-learning model, which was previously taught by other image-based databases, to learn how to determine the distance between various inputs using the features that were extracted. The proposed model is able to detect OSA using a 2D characteristics scalogram that was converted from a single-lead ECG signal.

### III. DATABASE AND PREPROCESSING

#### A. Database

For training in this study, the Totally Looks Like database [12] which contains 6016 pairs of paired images paired by humans as being visually similar was used. The extremely similar nature of each pair of images in this database helped the training of the Siamese network. For testing, we use the ECG recordings, which are from the PhysioNet 2000 challenge [13]. This dataset consists of 70 patients, and the recording of each patient is continuous for approximately 8 hours as the frequency is 100 Hz, and there is one annotation that indicates the presence or absence of apnea for each minute. These annotations were made by human experts.

#### B. Preprocessing

To reduce noise in ECG recordings, we used a bandpass third-order Butterworth filter with cutoff frequencies at 5 and 48 Hz filter to filter the ECG signal. Then, we can prepare to convert the 2D time-frequency scalogram of each minute ECG signal, as shown in Fig. 1. We transformed the time characteristic of ECG signals into a series of 2D scalogram representations by continuous wavelet transform (CWT) based on the Morlet wavelet in the time-frequency plane [14].

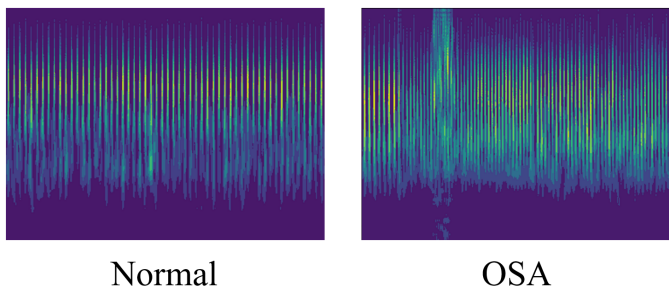


Fig. 1. 2D scalogram representation.

### IV. METHOD

Due to the ECG signals of different patients having strong individual differences, 3 samples were from the same patient for testing at one time, since there might not be many samples from one patient to train, we considered meta-learning, which is suitable for migration to small sample sets for each patient. Meta-learning was built to make the model acquire the ability of "Learning to learn" so that it can quickly learn new tasks based on acquiring existing knowledge.

At first, we used the Totally Looks Like database, which contains 6016 pairs of paired images by humans as being visually similar to train a Siamese network, which consists of three same deep neural networks and one connection unit to improve the ability to map extracted features to feature spaces [4]. During the training, three image samples were used as the input at the same time, one was marked as the anchor, the one that looked visually similar to the anchor was marked as positive, and the last sample, which was extracted randomly from the dataset will be marked as negative. Three samples were fed into the same neural network as a triplet to extract features as independent inputs. Fig. 2 shows an example of a triplet from the dataset Totally Looks Like during training. After obtaining the feature vectors  $f(X^p)$ ,  $f(X^a)$ , and  $f(X^n)$  of the three samples, the distance between the positive sample and the anchor point in the feature space was calculated as the difference between their feature vectors and then calculated the square of the binary norm to get the distance  $d^+$ . The distance between the negative sample and the anchor point was also calculated as  $d^-$  [4]. The calculation is shown in Fig. 3.

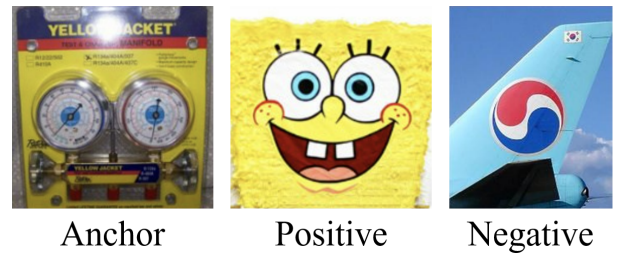


Fig. 2. An example of a triplet in training.

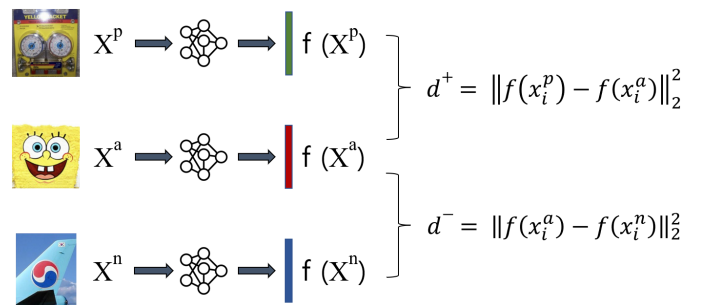


Fig. 3. Siamese network.

To accurately evaluate the distance of different categories of samples in the feature space, a trained neural network was supposed to have the following properties: feature vectors of the same category can be clustered together in feature space, and feature vectors of different categories can be separated, so  $d_+$  should be small because positive samples belong to the same category as anchor points, and  $d_-$  should be as large as possible [4].  $\alpha$  is a margin that is enforced between positive and negative pairs. The loss function in this Siamese network is given as:

$$\text{loss} = \|f(x_i^p) - f(x_i^a)\|_2^2 - \|f(x_i^a) - f(x_i^n)\|_2^2 + \alpha \quad (1)$$

As we trained the Siamese network well, to reduce individual differences, the one normal and one OSA sample from the same patient can be compared with the input sample from that patient, which we called a query. The two samples to compare with the query are called target samples. Since the number of each target sample for comparison is one, it is called one-shot prediction. A one-shot prediction determines the category of query based on the distance in the feature space between the query and the normal and OSA samples. The category of the query will be determined to belong to the target sample which has the closest distance to the query. For example, as shown in Fig. 4, because  $a \ll b$ , the category of the query was determined as normal.

## V. RESULTS AND DISCUSSION

To evaluate the proposed model, We used overall accuracy (AC), specificity (SP), sensitivity (SN), and F1 score to evaluate the performance, as defined below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (2)$$

$$\text{Specificity} = \frac{TN}{TN + FP} \quad (3)$$

$$\text{Sensitivity} = \frac{TP}{TP + FN} \quad (4)$$

$$\text{F1Score} = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \quad (5)$$

TP and TN are the abbreviations of true positive and true negative, and FP and FN denote false positive and false negative.

In the experiment, We used the ResNet-50 model with and without pre-trained weights on ImageNet to evaluate the distance in feature space between different samples. The 3 samples from the same triplet were from the same patient. 2000 triplets were tested to evaluate the performance of the proposed method.

As shown in Fig. 5, the proposed method with pre-trained weights achieved the performance with 68.10% accuracy, 69.19% sensitivity, 67.71% specificity, and 0.694 F1 score, which exceeds the method with pre-trained weights across the board. Based on the results, we can conclude that this method

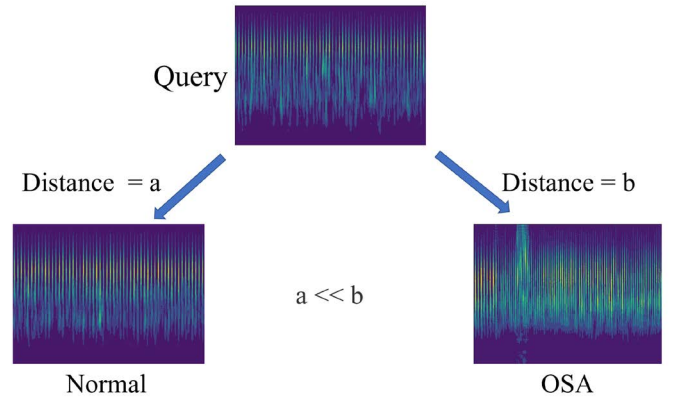


Fig. 4. One-shot prediction.

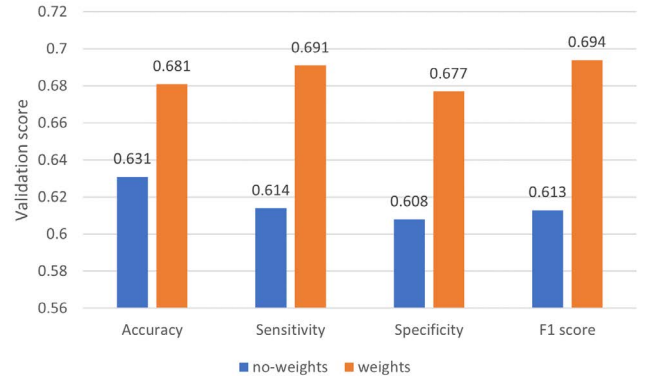


Fig. 5. Distributions of validation scores for the proposed models with and without pre-trained weights

is feasible to detect apnea from normal without training using massive OSA samples. The model based on Meta-learning reduces computation and does not rely on large amounts of samples compared to traditional machine learning. Because individual differences in ECG were considered, the sample from one patient only needs to be compared with the normal and OSA samples from the same patient. As the influence of individual differences on the classification of new patient samples is reduced, we are looking forward to the next method that can achieve better accuracy in the classification of obstructive sleep apnea and normal.

## VI. CONCLUSION

To reduce the impact of individual differences in different patients, this study proposed a method to detect OSA by meta-learning using a 2D time-frequency characteristics scalogram converted from a single-lead ECG signal by CWT. The achieved performance showed this method based on meta-learning using the Siamese network is feasible without being trained by massive 2D scalogram representations extracted from OSA signals.

In future work, we aim for a higher accuracy rate by new calculation of distance in feature space between different samples in the Siamese network. And since meta-learning

could be also used to do multivariate classification tasks as well, the accuracy of troubling classification problems between hypopnea and some subcategories, such as obstructive apnea, central apnea, and mixed apnea is looking forward to being improved.

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