

Recurrence Plot based Person Identification with ECG using CNN model

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Abstract— With the COVID-19 pandemic and an aging population, there has been a rise in demand for homecare for patients with chronic diseases that require continuous monitoring outside of the hospital. One important bio-signal for such monitoring is an electrocardiogram (ECG), which measures the electrical activity of the heart and can detect dangerous conditions such as arrhythmias and myocardial infarctions. The application of deep learning classification algorithms to arrhythmia and myocardial infarction diagnosis has gained interest. However, to be effectively utilized in everyday life, a method to determine who performed the measurement is necessary. In this study, we evaluated the use of recurrence plot pre-processing and convolutional neural network (CNN) models to identify individuals based on their ECG signals. Our proposed method demonstrated high accuracy results across various CNN models and was capable of identifying individuals.

Keywords— *Recurrence plot; Classification; Deep Learning; Electrocardiogram; Person identification; Convolutional neural network;*

I. INTRODUCTION

Development of deep learning, research for analyzing time series data are being studied significantly, and predicting weather and stock prices are general research field of time series. In addition, studies on fields such as bio-signals and various environmental data are being actively conducted, which are contributing greatly to the assistance daily living and healthcare fields. Especially, electrocardiogram (ECG) and photo-plethysmography time series bio-signals are used significant in deep learning research because they can be measured with simple sensors and various information can be extracted. ECG is a signal that measures the electrical activity of the heart, and it can be measured by attaching a patch-type sensor to the chest. In principle, the doctor should continuously monitor the ECG and analyze it whether an abnormal signal is found. However, as ECG data of arrhythmia and myocardial infarction are continuously accumulated, methods that can diagnose these symptoms are being studied with only deep learning algorithms. As an extension of the above studies, this study proposes a method that can identify a person only with ECG. We conducted this study based on the evidence that ECG signals have individual characteristics for each person [1]. The main contribution of this study is to suggest a method that measure and recognize at home or in everyday life as well as in hospitals. If this method is combined with ECG classification studies, it is possible to recognize the risk situation and who is measured at

the same time. In addition, the burden of time and cost required for medical personnel to continuously monitor the ECG can be reduced. There have been various approaches such as long short-term memory and machine learning to identify a person by ECG, and it has been shown that a person can be identified with high accuracy [2][3]. The difference from these approaches in this study is that we uses a recurrence plot (RP) as a preprocessing to extract ECG characteristics, and provides results that can identify people even from ECG data measured on different days using 2D CNN model. This paper describes in detail the method for converting ECG signals into a recurrence plot, and represents the results of person identification.

II. PROPOSED METHOD

To apply the ECG signal to the 2D CNN model, this time series signal must be converted into a 2D Image. In this chapter, a brief description of the ECG signal and how to convert it into an RP image are covered in detail.

A. ECG Signal

Representative signals of time series bio-signal are ECG, electroencephalogram, and photo-plethysmography. The ECG signal can be easily utilized because a vast data set is posted on the database. ECG generally has a form in which one large pulse and small pulses occur around it within one cycle. Variations in these rhythms or the waveform appearing as distorted, it can be analyzed as problematic. This study confirmed that the ECG signal differs in various factors such as peak, cycle, and small peak depending on the individual, so we use it to identify individual.

B. Recurrence Plot(RP)

RP is one of the advanced techniques for analyzing nonlinear data and can be used effectively for analyzing data with periodicity. Technically, RP is an imaged plot by drawing time series data on an m-dimensional spatial trajectory and using the distance between points located on each spatial trajectory. In general, the RP means a cross recurrence plot (CRP), and the calculated value is implemented to be expressed as 0 or 1 by applying the Heaviside function, It is shown in Equation (1) [4].

$$CRP_{ij} = \begin{cases} 1 & , \|\vec{x}(i) - \vec{x}(j)\| \leq \varepsilon \\ 0 & , \text{otherwise} \end{cases} \quad (1)$$

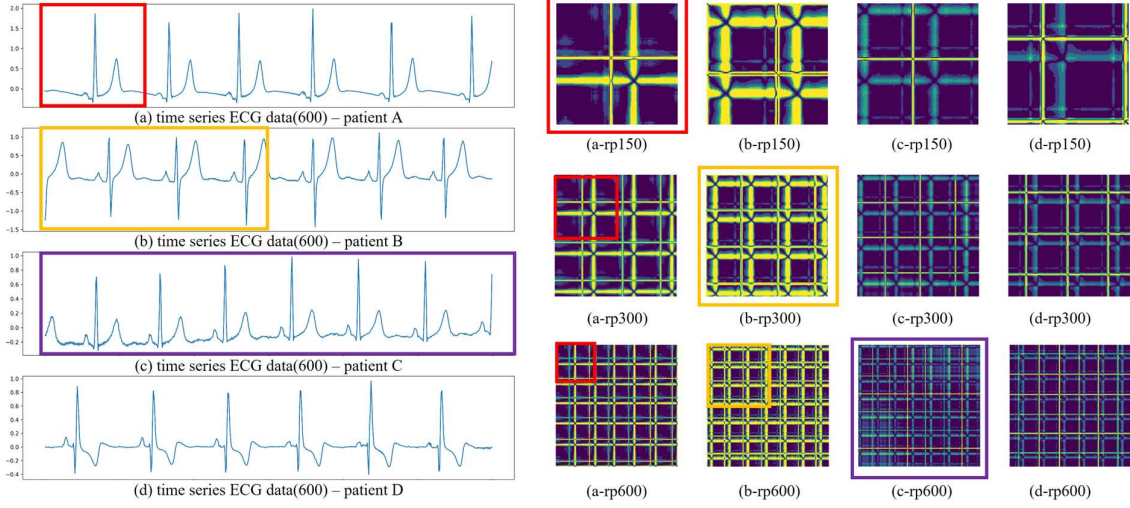


Fig. 1. time series ECG data and RP image according to slicing size; left- ECG data; right- {patient}-rp {slicing size}

In this study, in order to include more information in the RP image, we modify the RP equation to divide the ε value after removing the Heaviside function so that various numbers can be expressed.

$$RP_{ij} = \begin{cases} threshold_{ij}, & \frac{[\bar{x}(i) - \bar{x}(j)]}{\varepsilon} > threshold_{ij} \\ \frac{[\bar{x}(i) - \bar{x}(j)]}{\varepsilon}, & otherwise \end{cases} \quad (2)$$

This formula was expressed in Equation (2), and if the value after applying the formula is below the threshold value, the calculated value can be expressed as it is. The value of ε must be specified differently according to the data to be measured, and it is usually appropriate to determine it based on the peak value of the signal. In the case of using the ECG signal in the equation proposed in this paper, it is recommended to use a value between 5 and 8 for ε . The RP value of the ECG signal applied with this is shown in Figure 1. It is important to decide the hyper-parameters such as the threshold value and ε in the formula, but it is significant in a different sense to decide the slicing size. The slicing size can determine whether to emphasize data within one cycle or periodicity of several cycles in the time series signal to be analyzed. Fig.1 shows the ECG time series signals of 4 people and RP image from these data. The points of the expressed time series signal are 600, and the data measured for 6 seconds. The image converted to RP is the result extracted from 150, 300, and 600 slicing sizes. Figure 1-a-rp-150 is the result of converting 150 data into RP. As indicated by the red rectangle, since the signal of one period is represented by RP, information about the signals expressed within one period is strongly revealed. In contrast to this, Fig.1-a-rp300 becomes a result including 2~3 cycles, and data including periodicity appears. It can be seen that the RP in Fig.1-a-rp150 is expressed with 1/4 information. Finally, in Fig.1-a-rp600, the information of Fig.1-a-rp150 is expressed in a size of 1/16, and the information on the periodicity of data is emphasized rather than the information within one cycle. If there is no limit on the image input size, increasing the slicing size unconditionally can increase the accuracy, but this is impossible to apply deep learning model

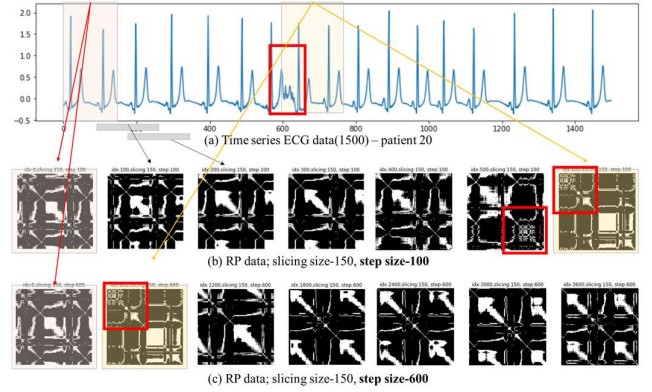


Fig. 2. Time series ECG Data & RP image; (a) 1500 slicing time series ECG data; (b) RP(slicing: 150, step: 100); (c) RP(slicing: 150, step: 600)

depending on computing power and performance. Therefore, it is necessary to limit the input size and we limit all image sizes to 75*75 or 150*150. We adopt a slicing size of 150/300/600 and analyzed it in a 2D CNN model after resizing. Fig.2 compares RP when the slicing size is 150 and the step size is 100 and 600. In Fig.2-(b), where the step size is 100, many recurrence plot images can be extracted, and all features can be extracted carefully. However, when the step size is 600 as shown in Fig.2-(c), the number of extracted images is small, but overfitting can be prevented as much as possible. We conducted an experiment with a step size of 200 to prevent overfitting while maximally extracting the features of the data.

III. EXPERIMENTS

A. Data Sets

In general, the diagnosis of sleep apnea is based on SpO2, a breathing signal analyzed by PPG [5]. However, SpO2 can also be measured with an ECG, and many ECG datasets are publicly accessible. We have used a publicly available database for person identification; The Apnea-ECG database [6]. The reasons we select this dataset is that everyone's measured data is

Table I. Validation and test results analyzed by 2D CNN model; test - evaluated by data measured after 4 weeks

Model	Metrics		RP Image shape: slicing-size(resizing-size)				
			300(75)	150(150)	300(150)	450(150)	600(150)
LeNet	#parameters		1,188,859	2,402,459			
	validation	accuracy	0.906	0.938	0.935	0.924	0.926
		loss	0.289	0.222	0.224	0.234	0.263
	test	accuracy	0.866	0.896	0.893	0.881	0.895
		loss	0.406	0.407	0.359	0.431	0.370
AlexNet	#parameters		21,800,379	30,189,691			
	validation	accuracy	0.844	0.894	0.890	0.870	0.886
		loss	0.449	0.316	0.309	0.387	0.337
	test	accuracy	0.794	0.856	0.853	0.839	0.838
		loss	0.575	0.403	0.430	0.488	0.487
VGGNet-16	#parameters		24,901,019	37,483,931			
	validation	accuracy	0.904	0.924	0.936	0.937	0.928
		loss	0.268	0.260	0.188	0.201	0.222
	test	accuracy	0.853	0.867	0.866	0.895	0.872
		loss	0.536	0.509	0.487	0.442	0.513
VGGNet-19	#parameters		26,228,763	38,811,675			
	validation	accuracy	0.901	0.940	0.932	0.882	0.939
		loss	0.319	0.234	0.223	0.365	0.211
	test	accuracy	0.847	0.891	0.871	0.818	0.887
		loss	0.576	0.459	0.487	0.589	0.451

measured over several hours or more. Most ECG datasets consist of data measured within 5 to 10 minutes, and if we select these datasets and using deep learning model, the result is highly likely to be overfitting. The Apnea-ECG database contains data from people of various genders, ages, and body types. All subjects were recorded for two consecutive nights, and then after an interval of four weeks, for two more consecutive nights. The ECGs is digitized at 100 Hz. We conducted a person identification experiment using the data from 55 people.

B. Results

Table 1 shows the results of evaluation with the CNN models after converting the ECG signal into RP. We use common 2D CNN models: LeNet, AlexNet, VGG16, and VGG19 [7][8]. The evaluated metrics are the number of parameters and validation, accuracy and loss in the validation/test datasets. The ratio of the dataset is training: validation: test = 1: 0.1: 0.1, and the test dataset is composed using data measured on different day from training/validation. The slicing size from which the RP image is extracted is 150/300/450/600, which is resized to 75/150 and used as input data. As a result, it is shown that LeNet can identify a person with the high accuracy even though the parameters are the lowest. In particular, it is a very meaningful result that people can be identified with an accuracy of nearly 90% even on the test dataset, which is the data measured over 8 hours continuously in daily sleep.

IV. CONCLUSION

In this study, we present a method for identifying people after converting ECG time series signals into RPs. Using a dataset measured over several hours continuously, which is not optimal data, we are able to identify 55 people even in the presence of many distorted signals. In particular, we show that we can identify people with an accuracy close to 90% even in the entire interval of data measured over 8 hours continuously in

daily sleep. To maximize the effectiveness of our proposed method, it would be ideal to measure, analyze, and identify people at the edge level. Therefore, we are working on optimizing the RP and reducing the size of the model while ensuring accuracy.

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