1D CNN Based Human Respiration Pattern Recognition using Ultra Wideband Radar

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***Abstract*— The respiration status of a person is one of the vital signs that can be used to check the health condition of the person. The respiration status has been measured in various ways in the medical and healthcare sectors. Contact type sensors were conventionally used to measure respiration. The contact type sensors have been used primarily in the medical sector, because they can be only used in a limited environment. Recent studies have evaluated the ways of detecting human respiration patterns using Ultra-Wideband (UWB) Radar, which relies on non-contact type sensors. Previous studies evaluated the apnea pattern during sleep by analyzing the respiration signals acquired by UWB Radar using a principal component analysis (PCA). However, it is necessary to measure various respiration patterns in addition to apnea in order to accurately analyze the health condition of an individual in the healthcare sector. Therefore, this study proposed a method to recognize four respiration patterns based on the 1D convolutional neural network from the respiration signals acquired from UWB Radar. The proposed method extracts the eupnea, bradypnea, tachypnea, and apnea respiration patterns from UWB Radar and composes a learning dataset. The proposed method learned data through 1D CNN and the recognition accuracy was measured. The results of this study revealed that the accuracy of the proposed method was up to 15% higher than that of the conventional classification algorithms (i.e., PCA and Support Vector Machine (SVM)).**

Keywords—UWB Radar, Vital Signs, Respiration Pattern, Healthcare, 1D Convolutional Neural Network

I. Introduction

The scope of health care has been expanded and, consequently, the technologies and device supporting it have are been diversified. Currently, in the healthcare field, wearable devices can measure vital signs such as heart rate and blood pressure and various services are provided based on the obtained data[1, 2]. However, wearable devices can be only used in a limited environment because they are basically composed of contact sensors. Moreover, it is hard to wear a wearable device for a long time. In order to overcome this shortcoming, healthcare devices using non-contact type sensors are emerging[3]. Since non-contact sensors can be installed around a user, it can provide services in a user-friendly environment. However, non-contact type sensors require sophisticated technologies because it is hard to acquire accurate information due to the interference between the sensors and people, which can be caused by external factors.

Ultra-Wideband (UWB) Radar is one of the non-contact sensors and it is capable of measuring various vital signs such as activity and respiratory status. Previous UWB radar-based vital sign measurement methods include a method of detecting apnea during sleep[4, 5, 6]. This technique can help the measurement of the quality of sleep or the determination of sleep disordered breathing (SDB). However, it is difficult to use it for measuring the quality of sleep or SDB because the simple measurement of apnea pattern does not provide sufficient data. Additionally, this method is based on the classical algorithm based on PCA, so there is a limit to improving the accuracy of it. The objectives of this study were to identify four different respiratory patterns (i.e., eupnea, bradypnea, tachypnea, and apnea) using UWB Radar and to suggest a method for detecting a breathing pattern based on 1D CNN.

II. UWB based Human Respiration Patterns

A. *Respiration Signal Measurement by UWB Radar*

The respiration signal is measured by detecting minute changes occurring when the ultra-wideband signal generated from UWB Radar is reflected on the chest and returns to the machine [7]. In other words, the thoracic cavity is expanded during inspiration as the air moves into the lung. Therefore, the UVW sensors get minutely closer to the subject. On the other hand, the distance becomes farther during expiration due to the shrinkage of the thoracic cavity. When these movements are measured by UWB Radar, inspiratory and expiratory can be detected (Fig. 1). During the measurement, the body of a subject must remain fixed. Otherwise, the distance between the sensors and the upper body of the subject is changed and the respiration signal cannot be measured accurately.

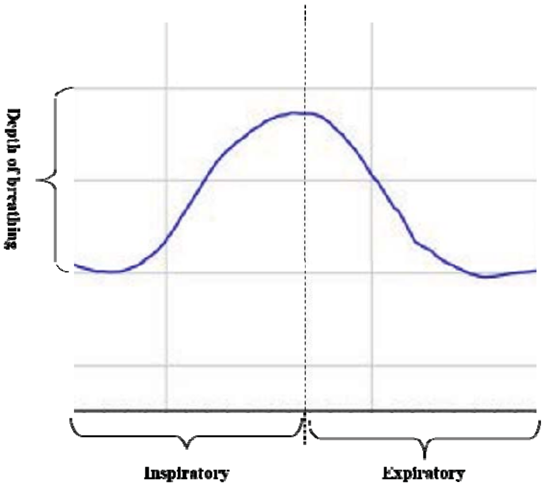

Figure 1. Expiratory and inspiratory in measurements

B. *Human Respiration Pattern and UWB Signal*

Respiration patterns can be classified into several types according to the number of respirations per minute. Moreover, it can be affected by age, the presence of a disease, body temperature, and emotion. This study classified the UWB signals into four respiratory patterns (i.e., eupnea, bradypnea, tachypnea, and apnea).

1) *Eupnea pattern*

The eupnea pattern refers to a condition that the mean respiration rate per minute is between 12 and 16 [8]. The respiration pattern of eupnea observed by UWB Radar is shown in Fig. 2(a).

2) *Bradypnea pattern*

The bradypnea pattern refers to a condition that the mean respiration rate per minute is equal to or less than 12. The respiration pattern of bradypnea observed by UWB Radar is shown in Fig. 2(b). When it is compared to the eupnea pattern, the depth of inspiration and expiration is lowered, and the respiration cycle is increased [8]. The bradypnea pattern is often observed during sleep and it can be caused by a disease.

3) *Tachypnea pattern*

The tachypnea pattern refers to a condition that the mean respiration rate per minute is equal to or more than 16. It may occur in the presence of illness (e.g., fever or weakness) or mental instability. It also can occur during a light exercise in the normal health condition [8]. The respiration pattern of tachypnea observed by UWB Radar is shown in Fig. 2(c).

4) *Apnea pattern*

Apnea is defined as the condition that a person shows a greatly reduced respiratory flow (more than 90% of the normal) for at least 10 seconds during sleep. Since the thoracic cavity does not shrink or expand during apnea, the body maintains a constant distance from UWB Radar [9]. As shown in Fig. 2(d), an inspiratory and expiratory respiration pattern is barely observed.

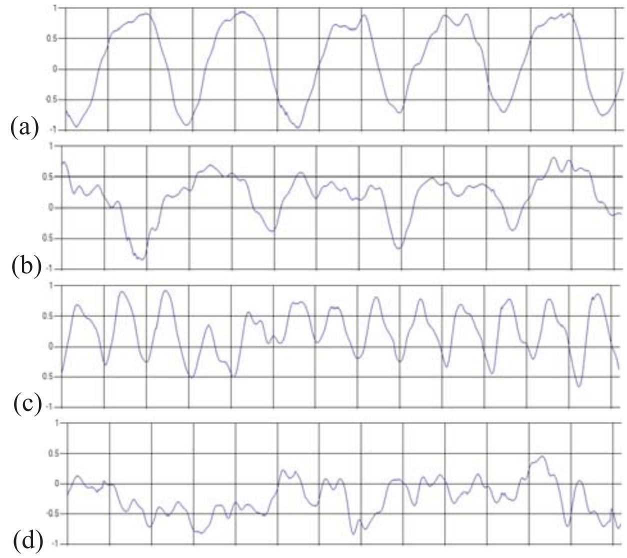

Figure 2. UWB Radar signals for the four respiration patterns (a: eupnea signal pattern, b: bradypnea signal pattern, c: tachypnea signal pattern, and d: apnea signal pattern).

III. 1D CNN BASED RESPRATION PATTERN RECOGNITION

The respiration signals obtained from UWB Radar are composed of one-dimensional data. Recently, 1D CNN is mainly used to detect patterns in data consisting of one-dimensional signals such as electrocardiography (ECG) sensors as well as UWB sensors [10, 11]. It is because it is possible to extract optimal features from the convolutional layer of the neural network for the classification. The conventional pattern recognition algorithms (e.g., PCA and SVM) generally require a pre-processing for extracting features. Therefore, this study modeled a neural network for recognizing four respiration patterns using 1D CNN. The layer structure and parameter setting consisted as follows from experiments.

A. *Layer Structure*

The layer structure of the 1D CNN, used for this study, is shown in Fig. 3. The convolutional layer was configured to generate feature maps over three times. Relu was used as an activation function, and robust features were selected through the max pooling layer between convolutional layers. Dropout was set as 0.4 while transferring the features extracted from the convolutional layer to the fully connected layer in order not to use some features randomly. The fully connected layer is composed of three convolutional layers. The last output layer is programmed to provide probability values for the four respiration patterns through Softmax.

B. *Parameters*

Three Kernel sizes were applied to the convolution layer. A relatively big Kernel size (1*31 size) was used for the first convolution layer. The Kernel size of the second convolution layer was about half of the Kernel used for the first layer (1*13 size). The last Kernel size was set as 1*3. Table 1 shows why the Kernel size was set to gradually reduce from the first one to

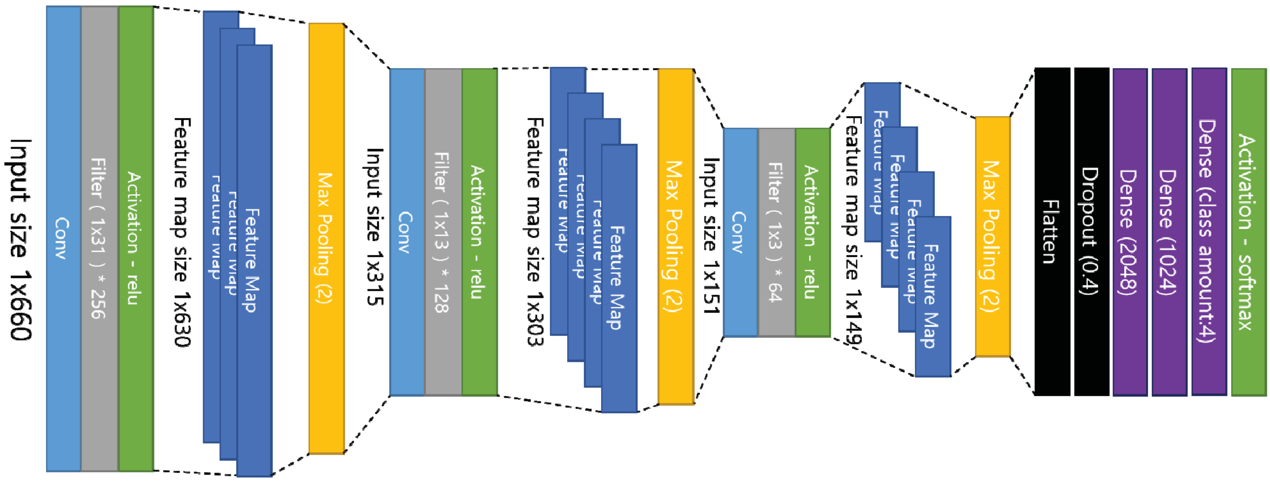

Figure 3. Schematic diagram of the 1D CNN layer structure and utilized parameter

the last one. It was confirmed that, when all Kernel sizes were too small or they are uniformly large, unnecessary features were extracted or the main features were lost to reduce the recognition rate. Therefore, this study set the Kernel size gradually reduced in order to remove noise in the first convolution layer, and to extract major features from the second and third convolution layers.

TABLE I. RECOGNITION RATE ACCORDING TO THE KERNEL SIZE APPLIED TO EACH CONVOLUTION LAYER

1st Convolution Layer	*2nd Convolution Layer*	*3rd Convolution Layer*	*Acc. (%)*
1 × 31	1 × 13	1 × 3	95.8
1 × 31	1 × 31	1 × 31	87.3
1 × 3	1 × 3	1 × 3	92.6

a. The best accuracy on different kernel size.

IV. EXPERIMENT RESULTS

This study compared the recognition rate of the conventional algorithm and that of the environment extracting the respiration signal of the four patterns using UWB Radar in order to conduct an experiment based on the proposed method. The UWB Radar respiration signal extraction was acquired by a subject artificially breathed to meet the definition of each pattern.

A. Experiment Environment

The data for learning was collected while the UWB Radar sensors and a subject were approximately 30cm apart. The specifications of UWB Radar used for collecting respiration signals are shown in Table 2.

TABLE II. UWB RADAR SPECIFICATIONS

Maximum Detecting Range	22m
Frequency Range	3.0 ~ 4.0 GHz
Bandwidth	0.45 ~ 1.0 GHz
Distance Resolution	1.5 ~ 3.3 cm
Antenna Angle	50°(X-Z plane) ~ 77.5°(Y-Z plane)

Collected respiration signals were classified according to the respiration rate per minute, measured by the UWB Radar sensors (Fig. 4).

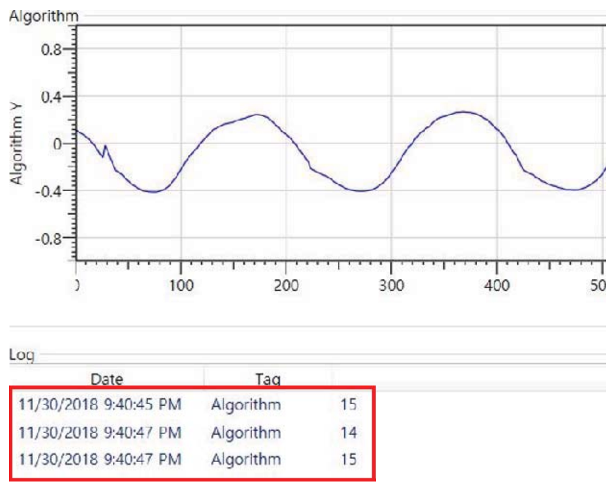

Figure 4. Confirmation of the respiratory rate per minute using UWB radar.

Three subjects participated in the data collection. One hundred datasets were collected for each pattern per person, so total 1,200 datasets were obtained (Table 3). One thousand datasets were used for neural network learning and the remaining 200 datasets were used for verification.

TABLE III. LEARNING AND VALIDATION DATASET COMPOSITION FOR EACH RESPIRATION PATTERN

Dataset	***Eupnea pattern***	***Bradypnea pattern***	***Tachypnea pattern***	***Apnea pattern***
Training set	250	250	250	250
Validation set	50	50	50	50

The results of learning and verification showed that, when the epoch reached approximately 30, the train accuracy was 1.0 and validation accuracy was 0.95.

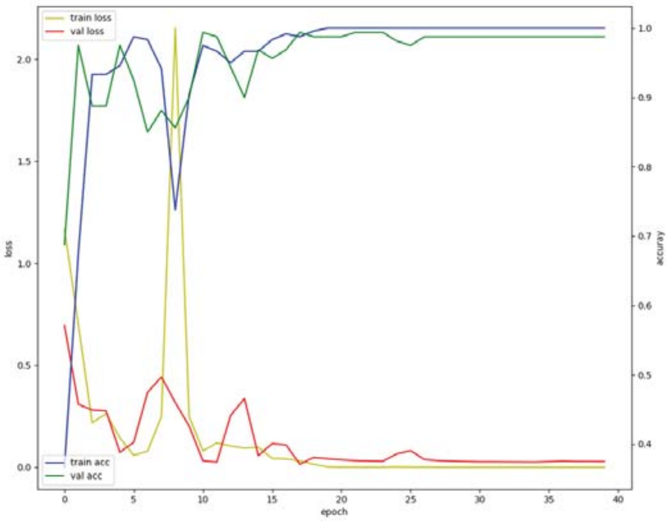

Figure 5. The learning and verification results of the proposed 1D CNN.

B. Accuracy Evaluation

In order to evaluate the accuracy of the proposed method, the recognition rate of the method was compared with that of the conventional classification method. The conventional classification method used a principal component analysis (PCA) and a support vector machine (SVM). The results showed that the accuracy of the proposed method was approximately 15% higher than that of the PCA method and approximately 8% higher than that of the SVM.

TABLE IV. COMPARISON OF RECOGNITION ACCURACY BETWEEN THE CONVENTIONAL METHOD AND THE PROPOSED METHOD

Methods	*The recognition rate of each breath pattern (%)*				*Average Acc. (%)*
	Eupnea	*Bradypnea*	*Tachypnea*	*Apnea*	
PCA	74.7	71.6	85.1	89.7	80.3
SVM	83.1	81.4	91.6	94.3	87.6
Proposed Method	94.7	92.5	97.2	98.6	95.8

In terms of the recognition results by pattern (Table 4), the conventional algorithms did not classify eupnea and bradypnea well, and the conventional methods had poorer recognition rates for eupnea and bradypnea than the proposed method. It is suspected that the conventional algorithms are limited in classifying these patterns because the respiration pattern of eupnea is very similar to that of bradypnea.

V. CONCLUSION AND FUTURE WORK

This study collected signal data for four human respiration patterns (i.e., eupnea, bradypnea, tachypnea, and apnea) using Ultra-Wideband (UWB) Radar and proposed a method to recognize the patterns using the proposed 1D CNN. The previous studies on UWB Radar based respiration status recognition methods have focused on methods to recognize apnea during sleep. It is necessary to recognize various respiration patterns of people including apnea in order to accurately identify the respiration status during sleep. The method proposed by this study can recognize more respiration patterns than conventional methods. Moreover, this study advanced the recognition rate by introducing a deep learning mechanism to the classification algorithm. We plan to optimize the main parameters (e.g., the number of filters, the size of a filter, and the number of layers) of the proposed 1D CNN in order to enhance the performance. We will also evaluate a method that can evaluate the quality of human sleep based on this optimization work.

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REFERENCES

[1] D. Dias and J. Paulo Silva Cunha, "Wearable Health Devices – Vital Sign Monitoring, Systems and Technologies", Sensors, Vol.18(8), July, 2018.

[2] O. Amft, "How Wearable Computing Is Shaping Digital Health", IEEE Pervasive Computing, Vol. 17(1), March, 2018.

[3] X. Hu and T. Jin, "Short-Range Vital Signs Sensing Based on EEMD and CWT Using IR-UWB Radar", Sensors, Vol. 16(12), September, 2016.

[4] Y. Maali, "An Automatic Sleep Apnea Analysis with Soft Computing Approaches", Faculty of Engineering and Information Technology, University of Technology, Sydney, September, 2014.

[5] G. Diraco, A. Leone and P. Siciliano, "A Radar-Based Smart Sensor for Unobtrusive Elderly Monitoring in Ambient Assisted Living Applications", Biosensors, Vol. 7(4), November, 2017.

[6] W. Yin, X. Yang, L. Li, L. Zhang and N. Kitsuwan, "Self-adjustable domain adaptation in personalized ECG monitoring integrated with IR-UWB radar", Biomedical Signal Processing and Control, Vol. 47, pp.75-87, January, 2019.

[7] V. Nguyen and M. A. Weitnauer, "Theoretical Spectral Analysis of the IR-UWB Radar Chest Reflection with Arbitrary Periodic Breathingand Heart-Induced Displacements", Electromagnetics Research B, Vol. 71, pp. 119-135, 2016.

[8] K. Mohan Rao and B. G. Sudarshan, "Design and Development of Real Time Respiratory Rate Monitor using Non-Invasive Biosensor", International Journal of Research in Engineering and Technology, Vol. 04, pp.437-442, June, 2015.

[9] Amerian Academy of Sleep Medicine, "The International classfication of sleep disorders: diagnostic and coding manual. 2nd Edition. Westchester", 2005.

[10] R. R. Karhe and Bhagyashri Badhe, "Heart Disease Classification Using One Dimensional Convolutional Nerual Network", International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering, Vol. 6, Issue 6, pp.88-95, June, 2018.

[11] Y. Chen and W. Chen, "Finger ECG based Two-phase Authentication Using 1D Convolutional Neural Networks", International Conference of the IEEE Engineering in Medicine and Biology Society(EMBC), October, 2018.