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Sleep Stage Classification using HRV parameters based on Recurrent Neural Network

깊은 인공신경망을 기반으로 심박변이율 지표를 이용한 수면 단계분석

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주 광 민

Abstract

Sleep Stage Classification using HRV parameters based on Recurrent Neural Network

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This study proposes a method of sleep stage classification using heart rate variability(HRV) and actigraphy features. ECG signals by heart rate monitor and actigraphy signal were measured during polysomnography (PSG). Total 19 features were inputted to artificial neural network classifier or recurrent neural network classifier. For training the model, the procedure finding optimal parameters which make the model accurately predict the sleep

stage was necessary and select the parameters resulting in best performance.

In this study, sleep stage was classified into 4 class, wake, rapid eye movement (REM) sleep, slow wave sleep (SWS) and light sleep. Many researches classified sleep stage into 3 class, wake, REM sleep, and NREM sleep, however detection of SWS has important roles in sleep physiology that reflect the recovery of tired brain and memory consolidation.

In the detection of wake stage, three method, sleep onset detection, long term wake detection and short wake detection, were performed. The result of one method was integrated with the result of other method. The method classified the wake stage with average sensitivity 51% specificity 92% Cohen's kappa 0.51 accuracy 85%.

In the detection of REM sleep and SWS, 5 models, linear discriminant analysis (LDA), k-nearest neighbor (kNN), support vector mahine (SVM), artificial neural network(ANN) and recurrent neural network(RNN) were applied as classifier. RNN classified the SWS stage with average sensitivity 64.7% specificity 97.4% Cohen's kappa 0.615 accuracy 89.8% and the REM stage

with average sensitivity 67% specificity 97% Cohen's kappa 0.60 , accuracy 91%.

For 4 stage classification, RNN classified the sleep stage with accuracy 71%, and kappa 0.52. The performance in each sleep stage detection and 4 stage classification were estimated by applying subjects in testing set.

Keywords : heart rate variability, recurrent neural network, sleep stage

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1. Introduction

1.1 Sleep in u-healthcare

U-healthcare means ubiquitous healthcare. Since a few decades, interest on u-healthcare in daily life has been increased steadily; besides, considerable researches of Healthcare in daily life have been studied. Sleep analysis as an area of u-healthcare includes sleep disorders, structure of sleep, and a pattern of sleep life. Recently, various sleep disorders such as obstruct sleep apnea(OSA), insomnia, and narcolepsy etc. have steadily increased, which implies the importance of monitoring individual sleep. In order to analyze individual sleep, we need to go sleep clinics or center of sleep in hospital and conduct nocturnal PSG. Currently, the gold standard of studying and analyzing sleep is PSG. However, PSG is expensive and needs a lot of sensors to be attached on subject's scalp and skin. Thus PSG is not appropriate for monitoring in long term. The most popular substitute for sleep monitoring at home is the actigraphy [1]. Because of limitation of actigraphy that misclassifies the stage in situation with low activity being awake, many researches with respect to sleep monitoring have studied using heart rate signal [2].

1.2 Classification Problems in Sleep study

Sleep stage classification has been studied mainly using electroencephalogram (EEG), bilateral electrooculogram (EOG), electromyogram (EMG), but also the number of studies using heart rate variability(HRV) were considerable. In studies using HRV, machine learning algorithms likes linear discriminant analysis(LDA) and support vector machine(SVM) as well as adaptive thresholding method were used for classification problem. The machine learning classifiers analyze the inputs supposed to be non-temporal signals. However, sleep structure is based on temporal signal which is affected by previous signal. Thus the classification method with effect of temporal feedback was needed.

In sleep stage classification using EEG, the artificial neural network has been used. The artificial neural network(ANN) has been applied to the various areas after multilayer perceptron neural network(MLPNN) was introduced and back-propagation training algorithm was developed[3] .

In this study, sleep stage classification was performed using ANN as classifier with HRV parameters. Among the various types of

ANNs recurrent neural network with connection between signals with the order in time domain was used to classify each sleep stage.

The machine learning classifier above mentioned have to select the features as input. Contrastively, ANN has the strength that doesn't have to select the features because it has the weighted connection between features. Moreover RNN could reflect the physiological characteristics with respect to continuous occurrence of rapid eye movement(REM) sleep and slow wave sleep(SWS).

2. Method

2.1 Subjects

In this study, nocturnal PSG data was recorded, also ECG and actigraphy was measured from 17 subjects. Table 2-1 shows the summary of sleep information about 17 subjects.

	Training subjects	Testing subjects
N	7	16
Sex(M/W)	4/3	7/9
Age(years)	37.6 ± 12.7	42.8 ±10.7
BMI(kg/m^2))	24.4 ± 3.5	24.2±7.2
Sleep onset latency(minutes)	13.0 ± 16.3	15.4±13.4
Stage Wake (minutes)	48.0 ± 28.8	42.4±29.8
Stage N1 & N2 (%)	60.6 ± 18.2	69.3 ± 11.6
Stage N3 (%)	10.3 ± 5.3	9.95±5.6
Stage REM (%)	21.26 ±3.1	20.0±5.0
Total sleep time(minutes)	353.0 ± 109.0	421.8 ± 30.6
Sleep efficiency (%)	85.98 ±6.8	88.0±6.6
AHI (events/hour)	7.2 ±5.6	7.6±4.3

TABLE 2-1 SUMMARY OF SUBJECT RELATED PARAMETERS FOR PSG

Data presented as mean ± standard deviation, AHI : apnea-hypopnea index,

BMI : body mass index, REM: rapid eye movement, OSA : obstructive sleep apnea

2.2 Data Acquisition

Nocturnal PSG of subjects participated in this study was conducted at the Center for Sleep and Chronobiology of Soul National University Hospital. PSG datasets were collected based on the standard PSG routine. Electroencephalogram (EEG) at C3-A2 and O2-A1, bilateral electroculogram (EOG), three electromyogram (EMG) at chin and anterior tibialis muscles. In addition to those, lead II ECG, abdominal and thoracic volume changes with piezoelectric-type belts, nasal airflow, body position, snoring, blood oxygen saturation were collected. Scoring of sleep stage was conducted by the trained sleep technicians according to AASM manual for 30-s epoch [4]. All signals were collected from NI-DAQ 6221 system(National Instruments, Austin, TX, USA) with 256-Hz sampling rate. Sleep parameters also were analysed; total sleep time(TST) is the amount of actual time of sleep period, sleep onset latency (SOL) is the time of first epoch scored as sleep satge, and sleep efficiency(SE) is the ratio of sleep time to the time in bed.

During nocturnal PSG, ECG signals and actigraphy signals were simultaneously measured by heart rate monitor with

accelerometer which is patch type while attached to torso (T_REX, Taewoong Medical, Korea). The device has tri-axis accelerometer(8g) and ECG signals with 256-Hz sampling rate. The dimensions and weight of the T-REX are 38 mm x 38 mm x 7 mm (W x D x H) and 10 g, respectively.

2.3 Signal Processing & Feature Extraction

In order to estimate sleep stage, it is important to extract the features related to physiological characteristics of each sleep stage. We extract various features from the electrocardiograph and actigraph signal. All of them were used as inputs of artificial neural classifiers , but only some of them were selected as inputs of machine learning classifier.

2.3.1 HRV

First, the ECG recordings acquired using Ag/AgCl electrodes at the sampling rate of 256 Hz. ECG raw signals were processed by band pass filtering at 35Hz of upper limit and 0.5Hz of lower limit. Here, 35Hz of upper limit is used to remove noises and signal' s base line. For ECG signal filtered by band pass, R-peaks were detected using automatic peak detection algorithm. Using R-R interval on the time domain , frequency domain, and nonlinear analysis, the parameters of Heart Rate Variability(HRV) were obtained.

HRV features were extracted from R-R intervals in window on 150 seconds interval. The window slides with forward steps of 30 seconds interval with respect to epoch in sleep study. In time

domain, 5 features were extracted. mHR means the average rate of heart beats in the window, SDNN means the standard deviation of NN intervals, which is related to the standard deviation of RR intervals [5]. RMSSD means the root−mean square differences of successive N−N intervals. pNN50 is the proportion of NN50 divided by total number of NNs. mHR_{var} is the variance of absolute difference between the raw mHR and the smoothed of mHR. We used the smoothing method in MATLAB (Mathworks 9.0.0. 341360 (R2016a)) as robust locally weighted scatterplot smoothing (rlowess) to adequately represent the changing pattern in respiration rate, which is a method for smoothing a scatterplot [6]. This is a type of weighted linear least−squares regression:

$$S = \sum_{j=1}^{N} W_{jj} r_j^2 \qquad \text{(eq. 1)}$$

where W is a weight matrix and r is the average respiratory rate. In frequency domain, VLF means the very low frequency from 0.0033 to 0.04 Hz. It is related to reflect the activity of sympathetic and parasympathetic nerve. The frequency bands are typically high frequency (HF) from 0.15 to 0.4 Hz, low frequency (LF) from 0.04 to 0.15 Hz. The nHF is normalized by the power of frequency band on 0.04 − 0.4 Hz and related to the activity of

parasympathetic nerve [7]. The LF is normalized by the power of frequency band on 0.04 – 0.4 Hz. The LF/HF means the ratio of LF with HF and is related with the activity of sympathetic nerve. The power of each frequency band was calculated by using Fast Fourier Transfrom(FFT).Applying HRV analysis based on the method of non-linear dynamics is reasonable considering complex mechanism of regulating heart rate. SD1 means the information of heart rate variability in short-term and also is related with the standard deviation of successive differences(SDSD). SD2 the information of heart rate variability in long-term and is related with SDSD, SDNN. SD1/SD2 is the ratio of SD1 with SD2 extracted by the non-linear method as Poincaré plot. The Approximate Entropy(ApEn)is inspired on measures of chaotic system that reflect irregularities of time series. Sample Entropy(SampEn) is a statistic to measure regularity of time series data. Alpha1 and alpha2 are short and long-term fractal exponents (alpha1 and alpha2) of the detrended fluctuation analysis (DFA).

To reduce the inter-subject deviation, all features mentioned above were normalized by subtracting the average and being

divided by standard deviation (eq. 2). After the normalization, new features smoothed using 'rlowess' method were used as the input of classifiers.

$$Feature_{Normalized} = (Feature - average(Feature))/std(Feature)$$

(eq. 2)

2.3.2 Electrocardiogram-Derived Respiration EDR

During REM sleep, physiological changes likes irregular amplitude and rate of respiration occur. Therefore, for classification of sleep stage, respiration signal is the useful signal. In this study, electrocardiogram-derived respiration(EDR) was extracted from ECG signal for respiration signal[8]. EDR can be extracted by various method, and among them it is popular to calculate of QRS complexes by using characteristics that amplitude of ECG is modulated by respiration[9 ,10]. In addition to method using amplitude, the calculation of EDR can be done by using characteristics that the interval of heart beats is short in inspiration but long in expiration by respiratory sinus arrhythmia (RSA)[11].

For extraction of EDR, the interval of R peaks(RR interval) was preprocessed by applying spline interpolation into 0.1 – 0.5 Hz frequency band using bandpass filtering. The frequency of the extracted EDR signal was calculated using auto correlation method in interval of 30s. The variance of EDR was calculated in interval of 150s. These signals was used as inputs in the classifier.

2.3.3 Actigraphy Features

Actigraphy signal in 3-axiswas extracted from T-REX with 32Hz sampling rate. The feature actually used was the magnitude of activity vector which is calculated by root of sum of squares of signals in each axis (eq. 3). Threshold was calculated using average magnitude in previous 4 epoch and post 4 epoch (eq.4-5).

$$Magnitude_{Actigraph} = \sqrt{(AccX^2 + AccY^2 + AccZ^2)} \qquad \text{(eq.3)}$$

$$\text{AverageAcc(i)} = Average\left(Magnitude_{Actigraph}\right) - median\left(Magnitude_{Actigraph}\right)$$

$$, i = 1,2, \dots, Last\ sleep\ stage \qquad \text{(eq. 4)}$$

$$\text{Threshold(k)} = \frac{1}{9}\sum_{j=k-4}^{k+4} AverageAcc(j) + \text{Average}\left(Magnitude_{Actigraph}\right)$$

$$\text{k} = 5,6, \dots, \text{Last sleep stage} - 4 \qquad \text{(eq.5)}$$

TABLE 2-2 All FEATURES OF HRV, EDR USED IN THIS STUDY

Analysis	Name	Explanation	Interval
Time domain	SDNN	standard deviation of NN intervals	150s
	RMSSD	the root-mean square differences of successive N-N intervals	
	mean HR	mean heart rate	
	mHR_{var}	variance of absolute difference between the raw mean HR and the smoothed of mean HR	
	EDR_{freq}	frequency of ECG derived respiration	30s
	EDR_{var}	variance of EDR_{freq}	
	ZCN_{X-axis}	number of zero crossing of X-axis	
	ZCN_{Y-axis}	number of zero crossing of Y-axis	
	ZCN_{Z-axis}	number of zero crossing of Z-axis	
	ACC_{pwr}	power of actigraph	
	EDR_{rate}	rate of ECG derived respiration	
Frequency domain	VLF	very low frequency from 0.0033 to 0.04 Hz	150s
	n LF	normalized low frequency (LF) from 0.04 to 0.15 Hz.	
	n HF	normalized high frequency (HF) from 0.15 to 0.4	
	LF/HF	Ratio of LF with HF	
Non-linear method	SD1n	normalized the information of heart rate variability in short-term	
	SD2n	normalized the information of heart rate variability in long-term	
	SD1/SD2	ratio of SD1 with SD2	
	ApEn15	approximate Entropy	
	SampEn15	sample Entropy	
	ApEn20	approximate Entropy	
	SampEn20	sample Entropy	
	Alpha1	short term fractal exponents of DFA	
	Alpha2	long term fractal exponents of DFA	

2.4 Design & Protocol

Figure 2-1 shows the protocol of sleep stage classification system used in this study. The protocol is composed of two steps, preprocessing step of data and classification step. Sleep stage is divided into 4 class stage, wake, REM, SWS, Light sleep. Each class of sleep stage was predicted by classifier or thresholding rule. After prediction of sleep stage, final 4 sleep stage was determined according to the descent order of performance.

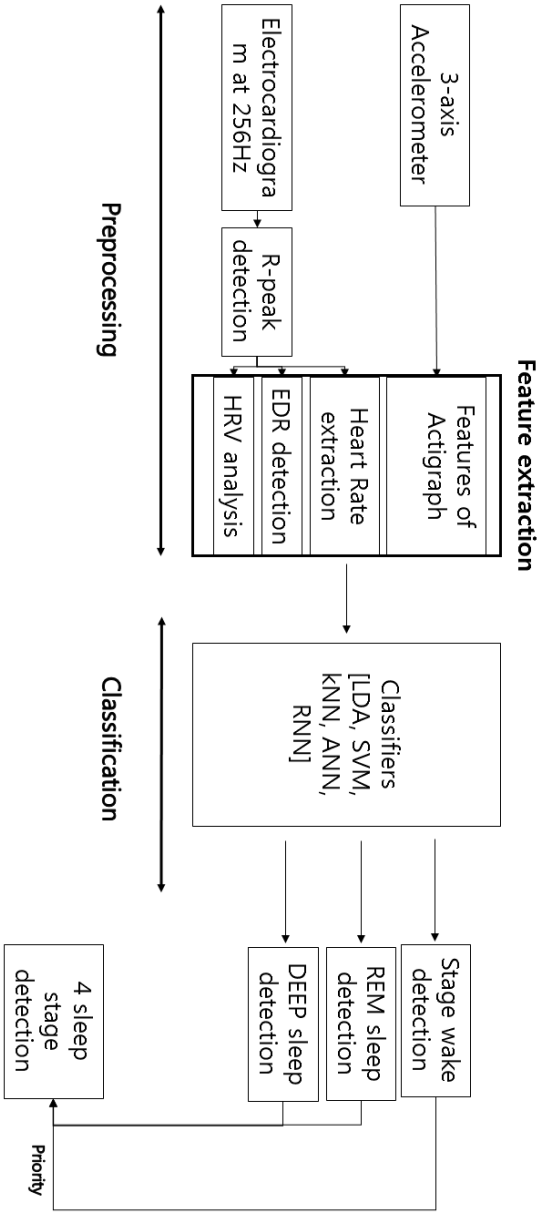

FIGURE 2-1 THE PROTOCOL OF SLEEP STAGE CLASSIFICATION

2.5 Supervised Learning

Supervised learning is one of machine learning methods as well as method finding the function classify the data with label. In supervised learning, each training data makes a pair with its label and outputs an estimated label. Therefore supervised learning makes the prediction function training the train data and applies to the test data. For an accurate prediction on test data, generalization procedure on a lot of train data is needed.

In this study, ANN and RNN is used as classifier. HRV and EDR features were named as X, input space and sleep stage label on each epoch were named as Y, output space. Above mentioned, the purpose of the ANN is find the prediction function, g.

$$g : X \rightarrow Y \qquad \text{(eq. 6)}$$

The function g is the element of all possible function set and the function f is a scoring function. The function g is determined by (eq.8).

$$f : X, Y \rightarrow R. \quad \text{R is real part} \qquad \text{(eq.7)}$$

$$g = \text{argmax}\,(f) \qquad \text{(eq. 8)}$$

2.6 Neural Classifiers

2.6.1 Artificial Neural Network

1) Definition

In general, modeling ANN is inspired from the biological nervous system, but ANN has a simple training structure. ANN has mainly used for pattern recognition, classification of signals and functional monitoring. The basic purpose of ANN is approximation of function, f mapping input X to category Y. Y is defined as (eq.9) and train parameter theta, θ to get best approximation.

$$Y = f(X\,;\,\theta) \qquad \text{(eq.9)}$$

ANN is called as feedforward neural network, because the information is propagate from input X to category Y by calculating units in neural network the through f. In this study, the model without feedback connection by itself is called as feedforward neural network and the model with feedback connection is called as recurrent neural network. In case of feedforward neural network with layers more than 2 layers, it is called artificial neural network(ANN).

2) Structure

The structure of ANN used in this study is shown in Figure 2-2. First layer is input layer and last layer is output layer which outputs the category on input data. ANN has hidden layer between input layer and output layer, which connects indirectly between input layer and output layer. Values in a layer called as units or neurons are calculated by an activation function. They are respectively weighted sum of neurons in previous layer. ANN has a fully connected weights. Figure 2-3 shows a procedure that the value of a hidden layer is determined. In (Eq.10), the value of input layer is weighted sum and summed with bias and final value is calculated through activation function.

$$\mathrm{h(x)} = f(b + \sum(w_i x_i)) \qquad \text{(eq.10)}$$

Total 19 HRV and EDR parameters are used as input of ANN; therefore the number of neurons in input layer is 19. Because prediction class is binary, the number of neurons in output layer is 2. For example, REM sleep and NREM sleep is predicted as '1' and '0'.

Parameters needed to select are max epoch, learning rate α, early stopping value μ, and the ratio of regularization γ. These parameters were determined in training procedure.

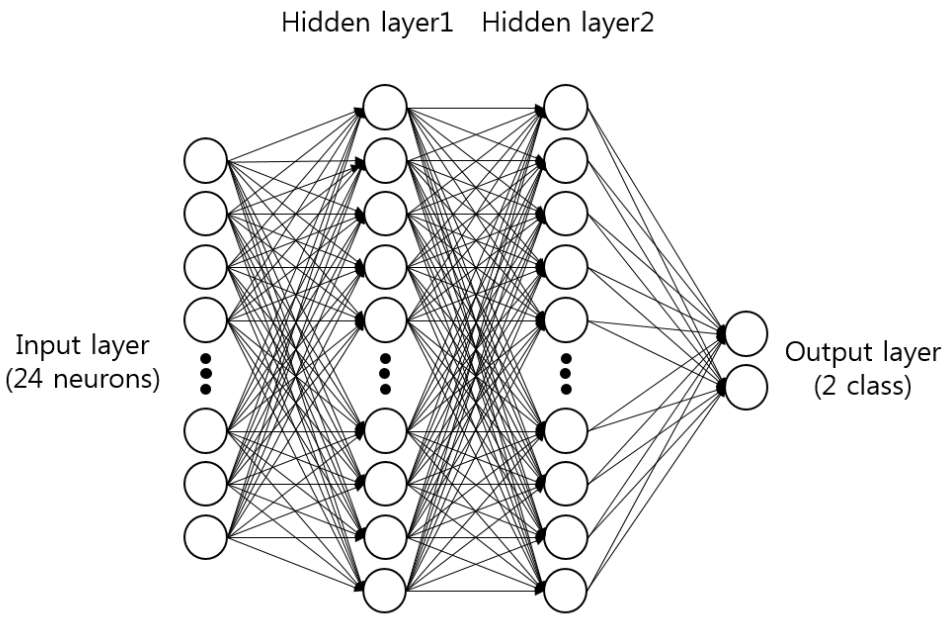

FIGURE 2-2 THE STRUCTURE OF ANN

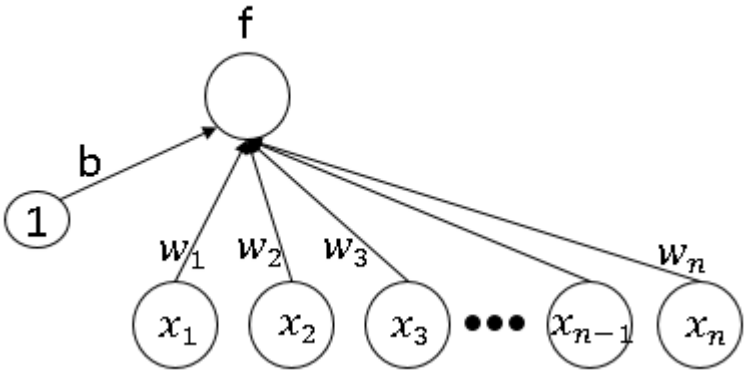

FIGURE 2-3 THE SCHEMATIC CALCUATION OF HIDDEN NEURON

f is activation function, b is bias, w is weight and x is input vector.

3) Training

First, training ANN requires making many of the same design decisions as are necessary for a linear model : choosing the optimizer, the cost function, and the form of the output units. Learning in ANN requires computing the gradients of complicated functions. In general, the back-propagation algorithm and its modern generalizations were used, which can be used to efficiently compute these gradients. Back-propagation adjusts the weights between layers and biases in each layer in neural network. The adjustment is performed using cost function comparing prediction value in output layer with label of input. Cost function is selected

as one of mean square error and cross-entropy.

Forward propagation that the inputs x provide the initial information that then propagates up to the hidden units at each layer and finally produces label y. In training procedure, forward propagation makes continuously scalar cost. On the contrary direction, backpropagation that makes information propagates down to input layer in order to calculate the gradient of error [12].

The basic concept of backpropagation is from gradient descent. Figure 2-4 shows that gradient descent updates in the direction of reducing the cost function. (eq.11) shows the procedure of gradient descent.

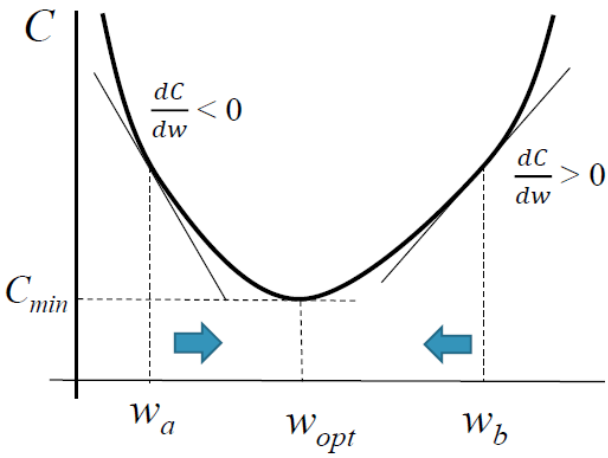

FIGURE 2-4 DESCRIPTION OF GRADIENT DESCENT

$$w_{n+1} = w_n + \Delta w = w_n - \eta \frac{dC}{dw}, \ \Delta w = -\eta \frac{dC}{dw} \quad \text{(eq.11)}$$

Δw is delta of weight, C is cost function, and η is learning rate

Backpropagation is abbreviation of backward propagation of errors and the common training method in artificial neural network. In Mathematical view, the procedure is followed (eq.12~20) [12]. **E** is the squared error, **t** is the target output for a training sample, and **y** is the actual output of the output neuron.

$$E = \frac{1}{2}(t - y)^2 \qquad \text{(eq.12)}$$

$$\mathbf{C}(\mathbf{w}, \mathbf{b}) \equiv \frac{1}{2n}\sum_x \|y(x) - a\|^2 \qquad \text{(eq.13)}$$

$$o_j = \varphi(y_j) = \varphi(\sum_{k=1}^{n} w_{kj} o_k) \qquad \text{(eq.14)}$$

Above equation, y_j is the weighted sum of outputs o_k of previous neurons. By chain rule, $\frac{\partial E}{\partial w_{ij}}$ can be expressed as (eq.15). Weights in every layer are updated change of weights as in (eq.20)

$$\frac{\partial E}{\partial w_{ij}} = \frac{\partial E}{\partial o_j}\frac{\partial o_j}{\partial y_j}\frac{\partial y_j}{\partial w_{ij}} \qquad \text{(eq.15)}$$

$$\frac{\partial y_j}{\partial w_{ij}} = \frac{\partial}{\partial w_{ij}}\left(\sum_{k=1}^{n} w_{kj} o_k\right) = o_i \qquad \text{(eq.16)}$$

$$\frac{\partial o_j}{\partial y_j} = \frac{\partial}{\partial y_j}\varphi(y_j) = \varphi(y_j)(1 - \varphi(y_j)) \qquad \text{(eq.17)}$$

$$\frac{\partial E}{\partial o_j} = \sum_{l \in L}\left(\frac{\partial E}{\partial y_l}\frac{\partial y_l}{\partial o_j}\right) = \sum_{l \in L}\left(\frac{\partial E}{\partial o_l}\frac{\partial o_l}{\partial y_l} w_{jl}\right) \qquad \text{(eq.18)}$$

$$\frac{\partial E}{\partial w_{ij}} = \delta_j o_j \qquad \text{(eq.19)}$$

$$\Delta w_{ij} = -a\frac{\partial E}{\partial w_{ij}} \qquad \text{(eq.20)}$$

Back-propagation algorithm in this study is a network training function that updates weight and bias values according to Levenberg-Marquardt optimization.

Like the quasi-Newton methods, the Levenberg-Marquardt

algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares, then the Hessian matrix can be approximated as

$$\mathbf{H} = \boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{J} \qquad \text{(eq.21)}$$

and the gradient can be computed as

$$\mathbf{g} = \boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{e} \qquad \text{(eq.22)}$$

where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix.

The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\boldsymbol{X}_{\boldsymbol{k+1}} = \boldsymbol{X}_{\boldsymbol{k}} - [\boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{J} + \boldsymbol{\mu}\boldsymbol{I}]^{-\mathbf{1}}\boldsymbol{J}^{\boldsymbol{T}}\boldsymbol{e} \qquad \text{(eq.23)}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift

toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced at each iteration of the algorithm.

Table 2-3 shows the training functions, activation functions, and performance function used in this study.

Category	Name
Backpropagation algorithm in training	Levenberg−Marquardt backpropagation
	Scaled conjugate gradient backpropagation
	Bayesian regularization backpropagation
Activation function	Elliot sigmoid function
	Hyperbolic tangent sigmoid function
	Rectified linear function Linear function
Performance function	Mean squared normalized error performance function
	Cross entropy

TABLE 2−3 TYPES OF FUNCTIONS USED IN TRAINING

2.6.2 Recurrent neural network

Recurrent neural network is the network with structure which has the connection between layers in different time step. It is known that RNN is more appropriate for time series data than feed forward neural network [13,14,15]. Simple recurrent network is Elman network designed by Elman that has input layer, hidden layer, output layer, and context layer and fixed back connection for maintaining hidden units of previous time step.

In this study, layer recurrent neural network was applied for classification. In the LRN, there is a feedback loop, with a single delay, around each layer of the network except for the last layer. The LRN command generalizes the Elman network to have an arbitrary number of layers and to have arbitrary transfer functions in each layer. Figure 2-5 shows the structure of RNN.

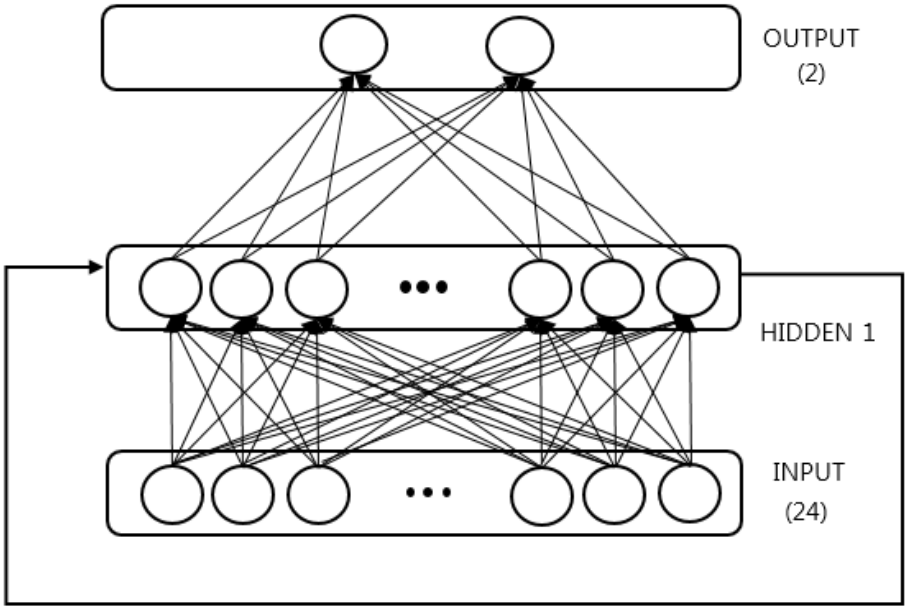

FIGURE 2-5 STRUCTURE OF RNN

2.6.2.1 Backpropagation through time (BPTT)

Backpropagation through time(BPTT) resembles the backpropagation in ANN. The significant difference is adding up gradient with respect to weight in each time step because RNN shares the weight among layers.

The error deltas of the output layer are represented in (eq.24). Each weight indicates that V is weight between the input layer and hidden layer, U is weight between the hidden layer and hidden layer, and W is weight between the hidden layer and output layer. W, V, and U are updated as (eq.25−27).

$$\boldsymbol{e_O(t) = d(t) - y(t)} \qquad \text{(eq.24)}$$

$$\mathbf{W(t+1) = W(t)} + \boldsymbol{\eta s(t) e_o(t)^T} \qquad \text{(eq.25)}$$

$$\mathbf{V(t+1) = V(t)} + \boldsymbol{\eta x(t) e_h(t)^T} \qquad \text{(eq.26)}$$

$$\mathbf{U(t+1) = U(t)} + \boldsymbol{\eta s(t-1) e_h(t)^T} \qquad \text{(eq.27)}$$

For BPTT training, error propagation is done recursively, then V and U updated as (eq.28−29).

$$\mathbf{V}(\mathbf{t}+\mathbf{1}) = \mathbf{V}(\mathbf{t}) \ + \ \boldsymbol{\eta} \sum_{z=0}^{T} \boldsymbol{x}(\boldsymbol{t}-\boldsymbol{z}) \boldsymbol{e_h}(\boldsymbol{t}-\boldsymbol{z})^{T} \qquad \text{(eq.28)}$$

$$\boldsymbol{U}(\mathbf{t}+\mathbf{1}) = \mathbf{U}(\mathbf{t}) \ + \ \boldsymbol{\eta} \sum_{z=0}^{T} \boldsymbol{s}(\boldsymbol{t}-\boldsymbol{z}-\mathbf{1}) \boldsymbol{e_h}(\boldsymbol{t}-\boldsymbol{z})^{T} \qquad \text{(eq.29)}$$

2.7 Regularization

Regularization is the method to improve generalization in machine learning. For generalization, overfitting have to be prevented. There are two methods used in this study, modifying the performance function and early stopping. Modifying the performance function is done by adding another term in original function. For example, when the performance function is mean squared error, the basic equation is below (eq.30−31).

$$\mathbf{F} = \mathbf{mse} = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2 \qquad \text{(eq.30)}$$

$$\mathbf{msw} = \frac{1}{n}\sum_{j=1}^{n} w_j^2 \qquad \text{(eq.31)}$$

The msw in (eq.32) means the mean of squared sums of the network weights and biases

$$\text{msereg} = \gamma \times \text{msw} + (1 - \gamma) \times \text{mse}$$

In this study, regularized mse was used by adjusting the performance ratio gamma.

When training a model for many iterations using gradient descent in machine learning algorithm, early stopping is the regularization method to avoid overfitting. Gradient descent updates the model' weight to be suitable for training data. When training models with

sufficient representational capacity to overfit the function, the error on training data decreases, but the generalization error often increases in a specific number of iterations. Thus early stopping is introduced to improve generalization. The training data was divided into 2 subsets, training set and validation set with 80% and 20%.

Training data subset was used to update the weights and biases and calculate the gradient of cost function. In training procedure, error was calculated for validation subset. When the validation error increases for a specified number of iterations. In the iteration the training is stopped, and the weights and biases at the minimum of the validation error are returned.

Among training method used in this study, Levenberg−Marquardt backpropagation makes cost function rapidly converge to minimum of the function. Therefore adjusting μ in (eq.23) was needed in training procedure.

2.8 Training and Testing

In this study, two subset was need to train the model and test the trained model. The method of leave one out cross validation that every subject of 17 subjects was selected as test data in each test process was applied. When ANN or RNN classifier was used, the number of iteration training the model was 5 times. That's because artificial neural classifier in this study established the random initial weights and biases. Thus, total number of training in each detection of sleep stage is 85 times.

2.9 Classification

In this study, the decision as to 4 sleep stages into which the test data are predicted was based on priority rules. First priority was in wake stage detection. REM sleep and SWS stage was marked in order of sleep stages with high performance in estimation, For example, the sleep stage with higher performance in estimation than other stage has the priority which determines the stage in later. Finally, the order of prediction of sleep stage was REM, SWS, and wake stage.

For detection of wake, REM, and SWS sleep and SWS using LDA, k-NN, SVM. ANN, RNN classifier, inputs were all features extracted in pre-processing of signals because of their characteristics to weight each feature.

After prediction, the post processing about estimation of REM and SWS was performed because REM and SWS have the characteristics that each stage is continuously marked.

2.10 Evaluation

Performance evaluation variables are used with estimating sleep stage. In table 5, there are several performance evaluation variables. The coefficient of Cohens's kappa is more reliable than accuracy in dealing with wake or REM or SWS stage classification because accuracy has a higher value in case of low true positive(TP) value.

	Description	Equation
Sensitivity	proportion of positives correctly identified as each stage	TP/(TP+FN)
Specificity	proportion of negatives correctly identified as each stage	TN/(FP+TN)
Accuracy	degree of closeness of measurement of true value	$\frac{\#\ of\ correct}{\#of\ total\ data}$
Coefficient of Cohen' s kappa	agreement between two raters who each classify N items into C mutually exclusive categories	$\frac{p_o - p_e}{1 - p_e}$

TABLE 2-4 PERFORMANCE ACCORDING TO PARAMETERS

3. Result

3.1 Wake detection

The wake stage was detected by 5 different classifiers, LDA, k-NN, SVM, ANN, RNN. Figure 3-1 shows the performance according to classifier. The best kappa performance for wake stage was by ANN.

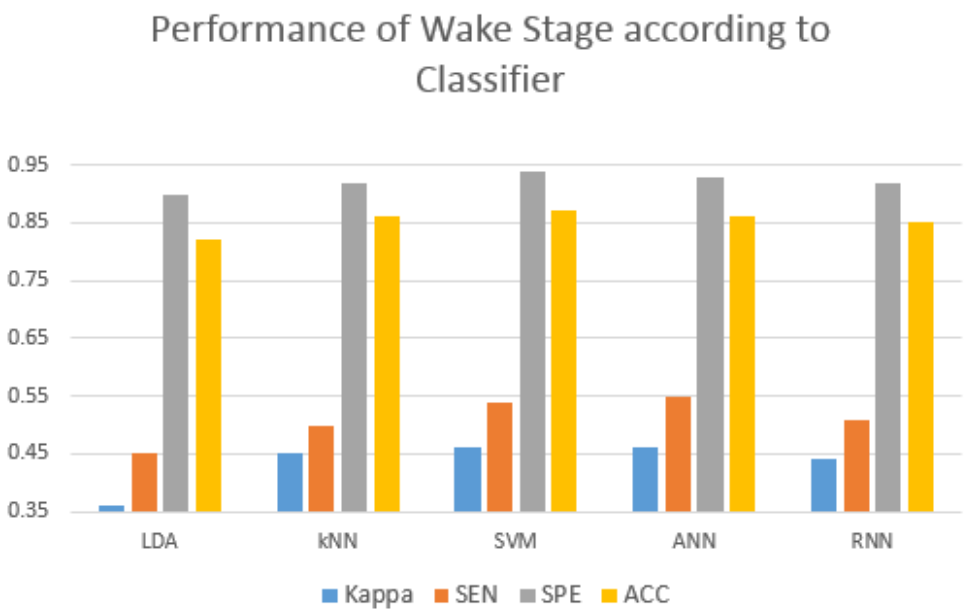

FIGURE 3-1 PERFORMANCE WAKE ACCORDING TO CLASSIFIER

Figure 3-2 shows the estimated wake stage and reference wake stage of subject 11 in testing set with best performance.

Table 3-1 shows the performance of every subject on wake stage detection, sensitivity, specificity, kappa, and accuracy.

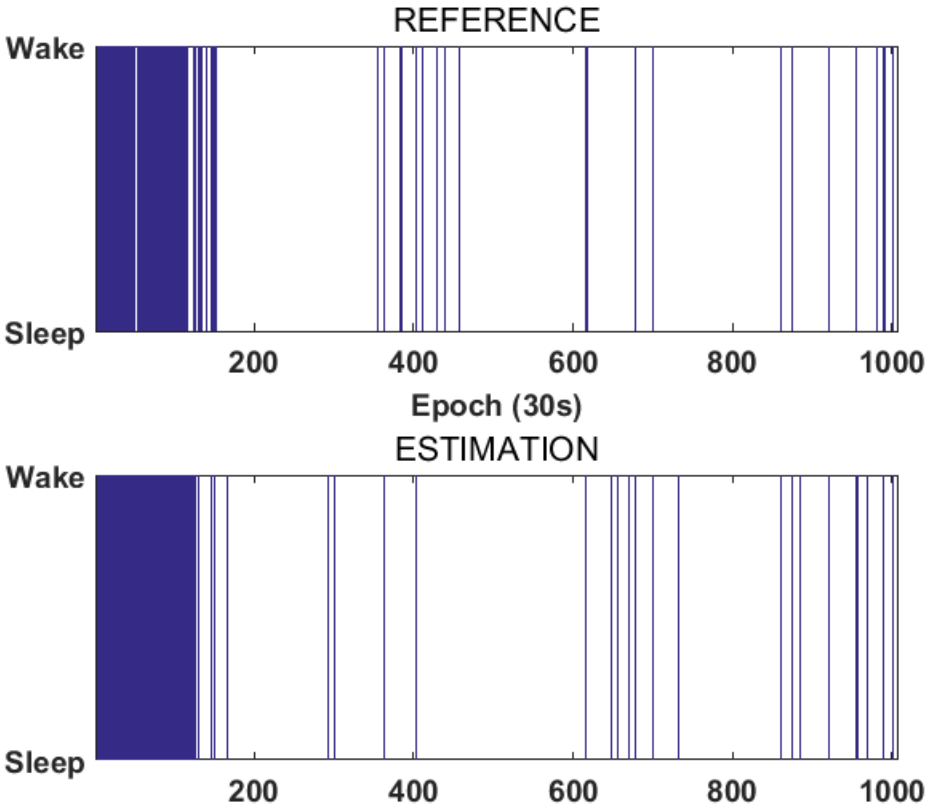

FIGURE 3-2 PLOT OF WAKE STAGE WITH BEST PERFORMANCE

	LDA	kNN	SVM	ANN	RNN
Kappa	0.36±0.17	0.45±0.14	0.46±0.15	0.46±0.14	0.44±0.12
Sensitivity	0.45±0.16	0.50±0.17	0.54±0.16	0.55±0.17	0.51 ±0.17
Specificity	0.90±0.02	0.92±0.03	0.94±0.02	0.93±0.02	0.92±0.02
Accuracy	0.82±0.07	0.86±0.04	0.87±0.06	0.86±0.05	0.85±0.05

Table 3-1 PERFORMANCE FOR WAKE STAGE OF EVERY SUBECT

3.2 REM sleep detection

3.2.1 Performance according to parameters

LDA, k-NN, and SVM was affected by the number of features as inputs. For comparison of the number of features, performance was calculated by adding features Figure 3-2 shows the performance according to the number of features by classifier.

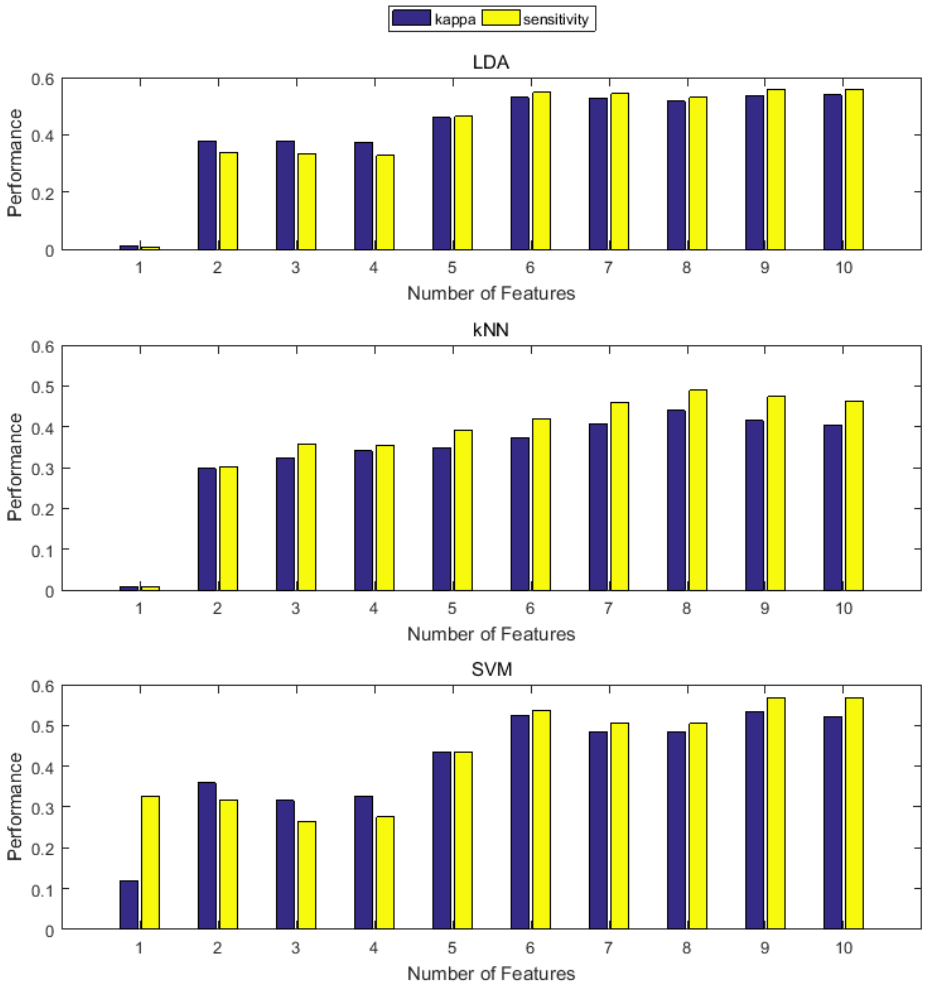

FIGURE 3-2 PERFORMANCE ACCORDING TO NUMBER OF FEATURES

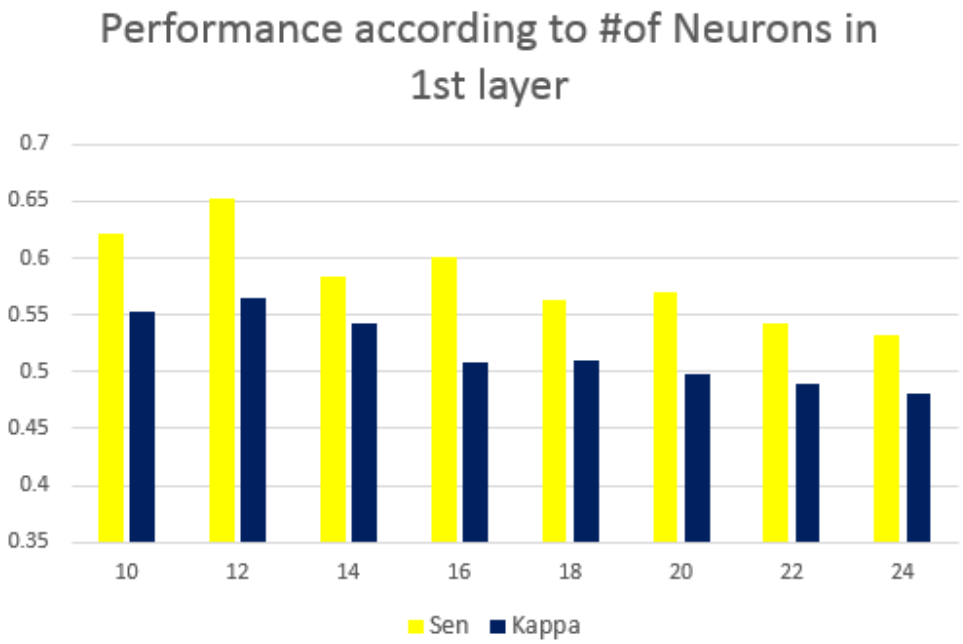

FIGURE 3-3 PERFORMANCE FOR REM ACCORDING TO NUMBER OF NEURONS of ANN

# of 1st Layer	# of 2nd Layer	Sensitivity (%)	Specificity (%)	Coefficient of Cohen's kappa	Accuracy(%)
10	5	0.67	0.97	0.60	0.91
	7	0.60	0.97	0.58	0.90
	9	0.60	0.96	0.56	0.88

TABLE 3-2 PERFORMANCE ACCORDING TO NUMBER OF NEURONS IN 2ND LAYER FOR RNN

Figure 3-3 shows the performance according to the number of neurons in first hidden layer of ANN. The performance of network with 12 neurons in first hidden layer and 7 neurons in second hidden layer was the highest values.

Table 3-2 shows the performance according to the number of neurons in second hidden layer of RNN. The performance of network with 10 neurons in first hidden layer and 5 neurons in second hidden layer was the highest values.

3.2.2 Performance according to classifier

Table 3-3 shows the performance according to classifier used to classify the REM sleep stage. The performance of RNN with 10 neurons in first hidden layer and 5 neurons in second hidden layer was the highest values. Figure 3-4 shows the performance according to classifier

	LDA	kNN	SVM	ANN	RNN
Kappa	0.52±0.24	0.44±0.19	0.53±0.25	0.56±0.13	0.60±0.18
Sensitivity	0.53±0.23	0.49±0.18	0.54±0.24	0.65±0.15	0.67±0.20
Specificity	0.96±0.04	0.93±0.04	0.96±0.04	0.96±0.02	0.97±0.03
Accuracy	0.88±0.05	0.85±0.05	0.88±0.05	0.89 ±0.04	0.91±0.04

TABLE 3-3 PERFROMANCE ACCORDING TO CLASSIFIER

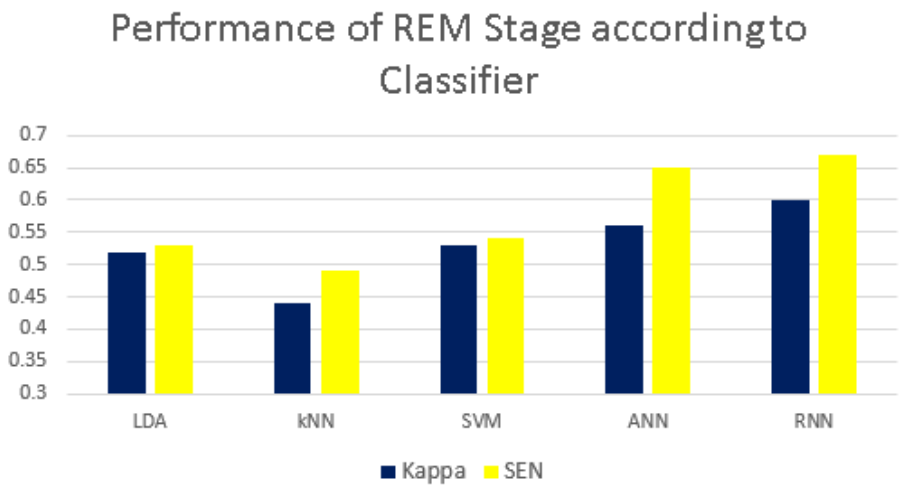

FIGURE 3-4 PERFORMANCE FOR REM OF CLASSIFIER

3.3 Slow wave sleep detection

3.3.1 ANN

LDA, k-NN, and SVM was affected by the number of features as inputs. For comparison of the number of features, performance was calculated by adding features Figure 3-2 shows the performance according to the number of features by classifier.

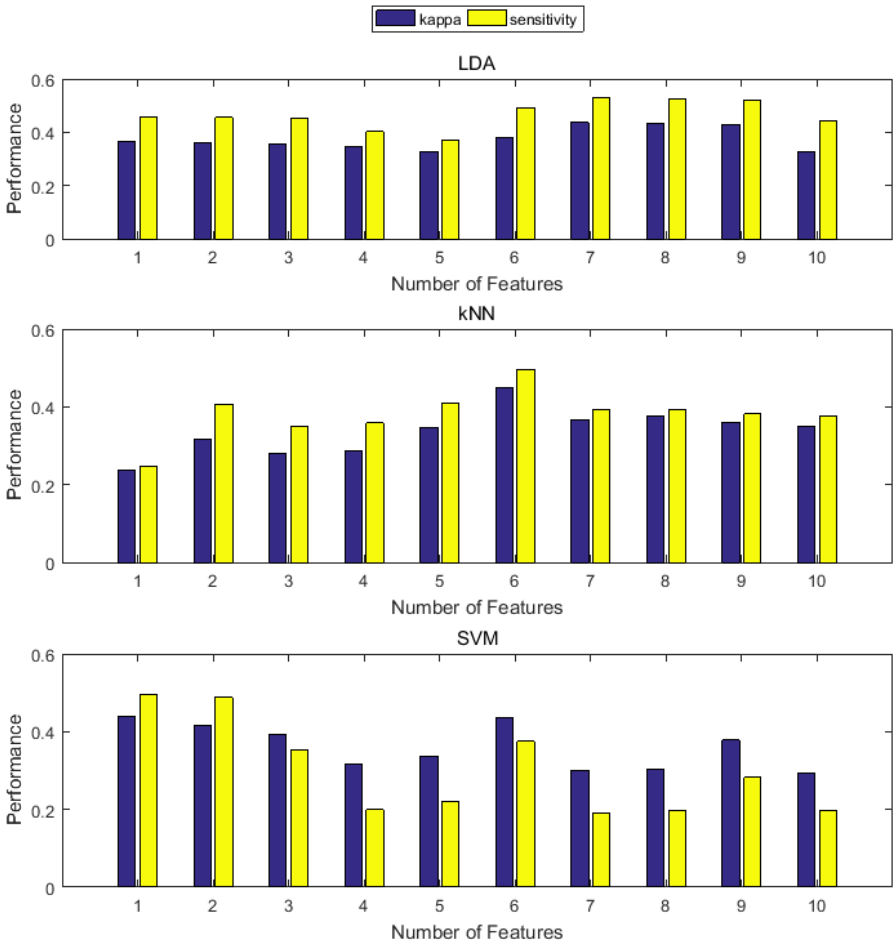

FIGURE 3-5 PERFORMANCE OF CLASSIFIER ACCORDING TO NUMBER OF FEATURES

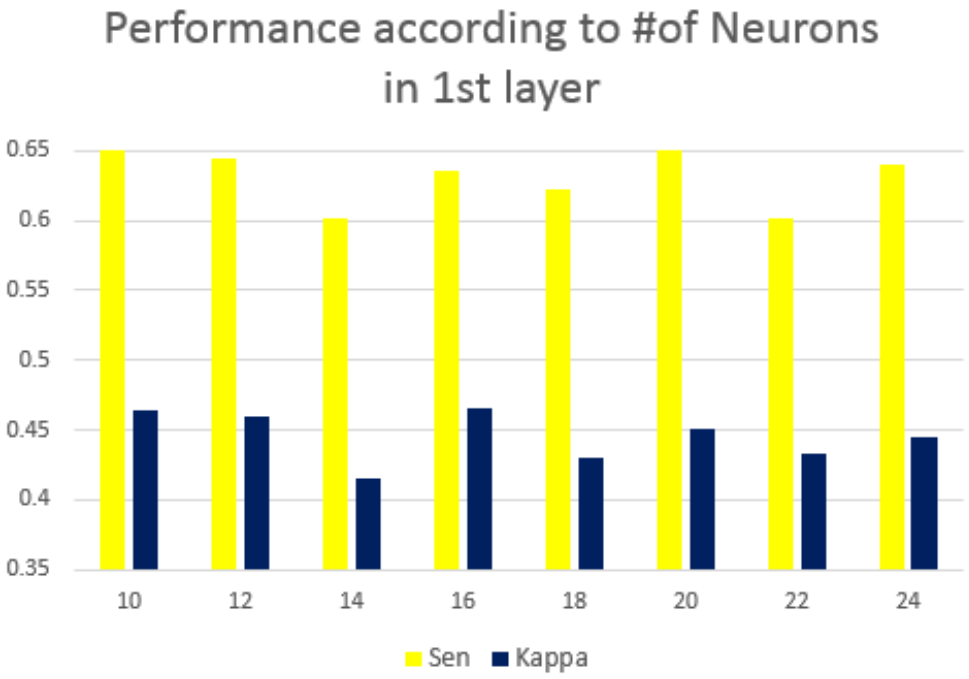

FIGURE 3-6 PERFORMANCE FOR SWS STAGE ACCORDING TO NUMBER OF NEURONS of ANN

# of 1st Layer	# of 2nd Layer	Sensitivity (%)	Specificity (%)	Coefficient of Cohen's kappa	Accuracy (%)
10	5	0.54	0.93	0.49	0.87
	7	0.56	0.97	0.51	0.90
	9	0.53	0.95	0.48	0.88

TABLE 3-4 PERFORMANCE FOR SWS ACCORDING TO NUMBER OF NEURONS IN 2ND LAYER FOR RNN

Figure 3-5 shows the performance according to the number of neurons in first hidden layer of ANN. The performance of network with 12 neurons in first hidden layer and 7 neurons in second hidden layer was the highest values.

Table 3-4 shows the performance according to the number of neurons in second hidden layer of RNN. The performance of network with 10 neurons in first hidden layer and 7 neurons in second hidden layer was the highest values.

3.3.2 Performance according to classifier

Table 3-5 shows the performance according to classifier used to classify the REM sleep stage. The performance of RNN with 10 neurons in first hidden layer and 5 neurons in second hidden layer was the highest values. Figure 3-7 shows the performance for SWS according to classifier

	LDA	kNN	SVM	ANN	RNN
Kappa	0.43±0.08	0.46±0.15	0.44±0.16	0.46±0.13	0.51±0.11
Sensitivity	0.52±0.17	0.49±0.19	0.49±0.23	0.55±0.24	0.56±0.15
Specificity	0.97±0.07	0.96±0.04	0.96±0.05	0.96±0.04	0.97±0.05
Accuracy	0.90±0.05	0.87±0.04	0.87±0.07	0.88±0.05	0.90±0.07

TABLE 3-5 PERFROMANCE FOR REM STAGE ACCORDING TO CLASSIFIER

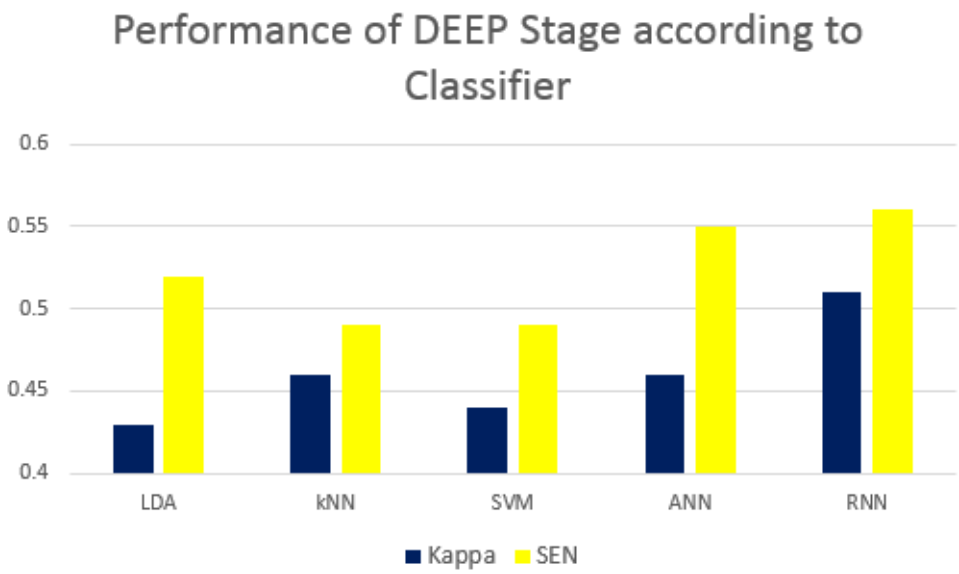

FIGURE 3−7 PERFORMANCE OF CLASSIFIERS FOR SWS STAGE

3.4 4 sleep stage detection

Figure 3-8 shows the performance for 3 sleep stage of classifier. The best performance was calculated from RNN classifier. Figure 3-9 shows the performance for 4 sleep stage of classifier. The best performance was calculated from RNN classifier.

Table 3-6 shows the performance of 16 subject in testing set for 4 stage classification. The accuracy is 0.715 ± 0.084 and kappa is 0.52±0.129

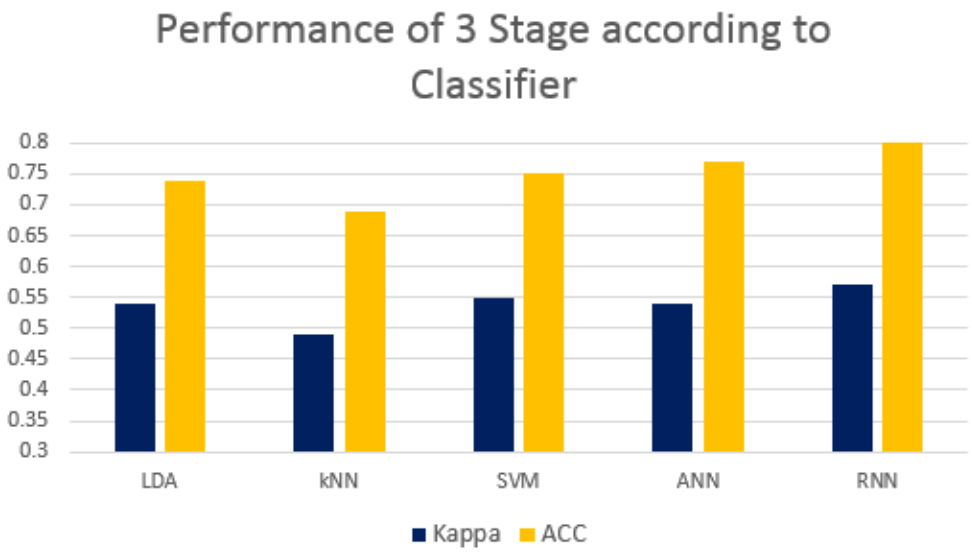

FIGURE 3-8 PERFORMANCE FOR 3 SLEEP STAGE OF CLASSIFIER

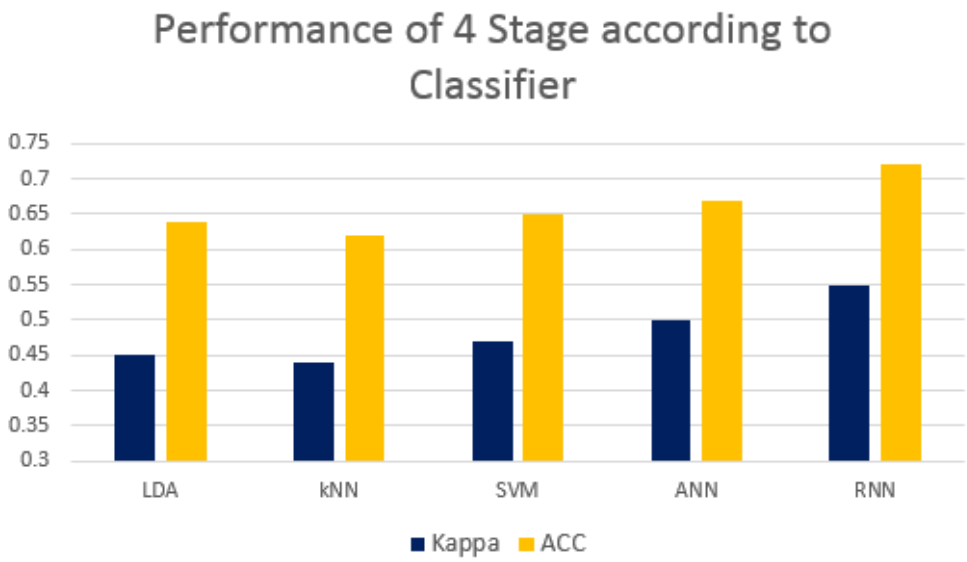

FIGURE 3−9 PERFORMANCE FOR 4 SLEEP STAGE OF CLASSIFIER

Subject #	Coefficient of Cohen's kappa	Accuracy (%)
1	0.775	0.862
2	0.548	0.712
3	0.604	0.803
4	0.684	0.822
5	0.43	0.623
6	0.517	0.698
7	0.369	0.667
8	0.41	0.636
9	0.399	0.609
10	0.791	0.88
11	0.455	0.742
12	0.41	0.602
13	0.556	0.719
14	0.396	0.717
15	0.493	0.651
16	0.522	0.688
Mean±SD	**0.523±0.128**	**0.715 ±0.084**

TABLE 3-6 PERFORMANCE OF 4 SLEP STAGE CLASSIFICATION

Table 3-7 shows the comparisons of result of sleep stage detection with previous studies. This study has better performance in 4 sleep stage classification than other studies.

Author(year)	Signal	Classifier	# of stage	# of subjects	Accuracy	Kappa
Meng. Xiao(2013)	ECG	Random Forest	WAKE REM NREM	45 healthy	72.58±6.70	0.4627±0.099
Redmond(2007)	ECG. Actigraphy	Quadratic / Linear discriminant	WAKE REM NREM	31	76	0.46
Milgliorini(2010)	BCG	Quadratic /Linear discriminant	WAKE REM NREM	17 healthy	76.81±7.51	0.55±0.10
Juha M. Kortelainen(2010)	BCG	HMM	WAKE REM NREM	18 healthy	79±10	0.44±0.19
T. Willemen(2014)	ECG, ACC, RESP	SVM(RBF)	WAKE REM LIGHT DEEP	85 healthy	69	0.56
Hwang(2015)	BCG	Adaptive threshold	WAKE REM LIGHT DEEP	19 healthy and OSA	71.3	0.48
This study	ECG. Actigraphy	ANN, RNN	WAKE REM NREM	16 healthy and OSA	80.1	0.57
			WAKE REM LIGHT DEEP		71.5	0.52

TABLE 3-7 COMRIOSONS OF REUSLT OF SLEEP STAGE DETECTION WITH PREVIOUS STUDIES

4. Discussion

In this study, the sleep classification method was proposed using artificial neural network and the evaluation for ANN and RNN with various structures was conducted. As a result, we classified sleep stage into 4 class for 17 subjects.

Many previous researches were mainly focused on the feature selection procedure for machine learning algorithms, but artificial neural network used in this study doesn't need the feature selection procedure. Also in the sleep stage classification studies using features from ECG or actigraphy, ANN and RNN are firstly introduced.

In this study, sleep stage was classified into 4 class, wake, rapid eye movement (REM) sleep, slow wave sleep (SWS) and light sleep. Many researches classified sleep stage into 3 class, wake, REM sleep, and NREM sleep.

RNN has the general limitation, called vanishing gradient that long term relationship with data. Therefore, one of recurrent neural network ,long-short term memory (LSTM) could show better performance than simple recurrent neural network.

5. Conclusion

In this study, the design of sleep classification method was presented and established. Especially for REM sleep and SWS, modeling the neural network classifying the sleep stage and using the features from ECG and actigraphy was proposed and evaluated.

Finally, the method using RNN for classifying the sleep stage as 4 and 3 classes shows higher performance than other studies. This results shows that RNN is appropriate for classification of sleep stage.

As a result, we confirmed that using neural network as classifier doesn't need the feature selection procedure and RNN is appropriate for time series data.

6. Reference

[1] V. Natale, G. Plazzi, and M. Martoni, "Actigraphy in the assessment of

insomnia: A quantitative approach," Sleep, vol. 32, pp. 767–771, 2009.

[2] A. Sadeh and C. Acebo, "The role of actigraphy in sleep medicine," Sleep Med. Rev., vol. 6, pp. 113–124, 2002.

[3] Akin, M.; Kurt, M.; Sezgin, N.; Bayram, M. Estimating vigilance level by using EEG and EMG signals. Neural Comput. Appl 2008, 17, 227–236.

[4] C. Iber, S. Ancoli-Israel, A. Chesson, and S. F. Quan, The AASM Manual for Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specification. Westchester, IL: American Academy of Sleep Medicine, 2007.

[5] M.P. Tulppo, T. Makikallio, T. Takala, T. Seppanen, and H.Huikuri, "Quantitative beat-to-beat analysis of heart rate dynamics during exercise," American Journal of Physiology-Heart and Circulatory Physiology, vol. 40, no. 1, pp. H244,1996.

[6] Cleveland W S 1979 Robust locally weighted regression and

smoothing scatterplots J. Am. Stat. Assoc. 74 829–36

[7] M. Malik, J.T. Bigger, A.J. Camm, R.E. Kleiger, A. Malliani,A.J. Moss, and P.J. Schwartz, "Heart rate variability standardsof measurement, physiological interpretation, and clinicaluse," European heart journal, vol. 17, no. 3, pp. 354–381,1996.

[8] D. Widjaja, J. Taelman, S. Vandeput, M. A. Braeken, R. A.Otte, B. R. Van den Bergh, and S. Van Huffel, "Ecg–derivedrespiration: Comparison and new measures for respiratoryvariability," Computing in Cardiology, pp. 149–152, 2010.

[9] J. Jo, A. Blasi, E. Valladares, R. Juarez, A. Baydur, and M.Khoo, "Determinants of heart rate variability in obstructivesleep apnea syndrome during wakefulness and sleep," AmericanJournal of Physiology–Heart and Circulatory Physiology,vol. 288, no. 3, pp. H1103–H1112, 2005.

[10] P. de Chazal, C. Heneghan, E. Sheridan, R. Reilly, P. Nolan, and M.O' Malley, "Automated processing of the single–lead electrocardiogram for the detection of obstructive sleep apnoea," IEEE Trans. Biomed. Eng., vol. 50, no. 6, pp. 686–696, Jun. 2003.

[11] J.A. Hirsch, and B. Bishop, "Respiratory sinus arrhythmia in

humans: how breathing pattern modulates heart rate," Am J Physiol, vol. 241, no. 4, pp. H620-H629, 1981.

[12] Rumelhart, D., Hinton, G., and Williams, R. (1986a). Learning representations by back-propagating errors. Nature, 323, 533-536. 13, 17, 22, 198, 213, 358, 459, 465

[13] K.I.Funahashi, Y.Nakamura, Approximation of dynamical systems by continuous imerecurrentneuralnetworks,,NeuralNetworks6(6)(1993) 801-806.

[14] .A.Feldkamp, G.V.Puskorius,Asignalprocessingframeworkbasedon dynamic neuralnetworkswithapplicationtoproblemsinadaptation, filtering, andclassification,Proc.IEEE86(11)(1998)2259-2277.

[15] M.H usken, P.Stagge, Recurrent neural networks for time series classification , Neurocomputing 50(2003)223-235.

[16] Colrain IM, Trinder J, Fraser G, Wilson G. Ventilation during sleep onset. J Appl Physiol 1987:63; 2067-74.

국문 초록

깊은 인공신경망을 기반으로 심박변이율 지표를 이용한 수면 단계분석

본 연구는 심박변이율과 액티그래프 데이터를 이용하여 사람의 수면단계를 분석하는 순환형 인공신경망 기술을 제안하였다. 순환형 인공신경망은 순차적 데이터를 처리하는 경우에 용이하며, 필기체 인식, 자동번역, 음성신호인식 등에 많이 이용되어왔다. 최근에는 뇌파나 시간 축을 기반으로 하는 생체신호를 대상으로 순환형 인공신경망이 많이 적용되어왔고 본 연구에서는 심박변이율 데이터를 최초로 적용하였다. 심박변이율을 추출하기 위해 쓰인 심전도신호와 액티그래프 신호는 23명을 대상으로 한 야간 수면 다원검사를 실시하는 동안 측정되었다. 심박변이율 지표와 액티그래프를 이용한 지표를 포함하여 총 24개의 지표가 순환형 인공신경망의 입력 값으로 이용되었다. 본 연구에서 제안한 방법의 성능을 다른 방법과 비교하기 위하여 지지벡터머신, 선형분리법, k최근접이웃, 다층 인공신경망을 동시에 적용하고 순환형 인공신경망과 비교하였다. 모델을 훈련하는 과정에서 정확한 수면단계를 추정할 수 있는 최고의 성능을 내는 최적의 파라미터를 찾기위한 과정을 거쳐 파라미터를 선정하였다.

본 연구에서는 수면 단계를 총 깸, 렘 수면, 서파 수면 그리고 얕은 수면으로 총 4단계로 분류하였다. 기존의 수면단계를 분석하는 많은 연구에서는 수면단계를 깸, 렘수면, 그리고 비렘수면으로 총 3단계분석이 많이 이루어졌다. 하지만 서파수면은 피곤에 지친 뇌의 회복과 기억응고화를 반영한다는 수면생리학에서 중요한 역할을 맡고 있다. 따라서 총 4단계분석을 통하여 서파수면까지 측정하는 것이 보다 의미가 있다.

각 수면단계를 분류하는 일에서 인공신경망은 다른 머신러닝 알고리즘에 비해 지표를 선정하는 작업을 거치지 않아도 된다는 장점이 있다. 따라서 다층 인공신경망과 순환형 인공신경망을 이용해 단계를 분류하는 과정에서는 지표 선정없이 모든 지표를 입력 값으로 입력하였다. 하지만 지지벡터머신, 선형분리법, 그리고 k최근접이웃과 같은 머신러닝 방법을 이용할 때는 지표를 순위를 매겨 선정하는 알고리즘을 거친다.

순환형 인공신경망을 이용했을 때, 깸 단계를 분석한 결과 모든 피험자에 대한 평균 민감도는 51%, 특이도는 92%, Cohen’s kappa 는 0.51, 그리고 정확도는 85%가 나왔다. 렘수면 단계를 분석한 결과는 평균 민감도가 67%, 특이도가 97%, Cohen’s kappa가 0.60, 그리고 정확도가 91%가 나왔다. 서파수면 단계를 분석한 결과는 평균 민감도가 56%, 특이도가 97%, Cohen’s kappa가 0.51, 그

리고 정확도가 91%가 나왔다. 각 수면 단계에 우선순위를 깸, 렘 수면, 서파 수면, 그리고 얕은 수면 순으로 두고 수면단계를 총 4단계로 분류하였다. 4단계 분석 결과는 Cohen’s kappa가 0.52, 그리고 정확도가 71%가 나왔다. 기존 연구에 비하여 더 우수한 성능을 보여주었다는 점, 기존 방식과 다르게 지표선정과정을 없이 수면단계를 분류했다는 점, 그리고 시간에 의존된 정보를 추출할 수 있는 순환형 인공신경망을 적용했다는 점에서 본 연구의 성과를 찾을 수 있다.

주요어 : 심박변이율, 순환형 인공신경망, 수면 단계

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