Learning and Recognition with Neural Network of Heart Beats Sensed by WBAN for Patient Stress Estimate for Rehabilitation

Yukihiro Kinjo[1], Yoshitomo Sakuma[2], and Ryuji Kohno[3]

[1] Graduate School of Engineering Science, Yokohama National University, Yokohama, Kanagawa 240-8501, Japan
kinjo-yukihiro-vm@ynu.jp
[2] Graduate School of Engineering Science, Yokohama National University, Yokohama, Kanagawa 240-8501, Japan
sakuma-yoshitomo-cm@ynu.jp
[3] Graduate School of Engineering Science, Yokohama National University, Yokohama, Kanagawa 240-8501, Japan
kohno-ryuji-ns@ynu.ac.jp

Abstract. Detecting patient stress in rehabilitation is important to improve a manner of rehabilitation with less stress. To estimate patient stress or emotion by rehabilitation training, we introduce machine learning with neural network(NN) of which the input is R-R interval(RRI) of ECG or heart rate data sensed by Wireless Body Area Network(WBAN) and the output is judgement if the patient left stress or not. However, machine learning processing needs big data and a large amount of computational complexity and sending heart rate data via cloud network to AI server computer like Watson for machine learning processing which costs much and causes network delay. In this research, we propose how to reduce computational complexity to enable to calculate by limited processing power in embeded processor of BAN cordinator. Specifically, we aim to reduce it to use NN with preprocessing by wavelet transform and extraction of coefficient of variance of RRI,i.e. CVRR. Preprocessing extract a part of feature before NN processing and computational complexity by NN processing reduce.

Keywords: WBAN · neural network · emotion recognition

1 Introduction

In rehabilitation, not only the categorical approach based on patient's disability but also the individual approach that takes patient's personality into account is important in order to apply high quality rehabilitation to patients and aim for early recovery[1]. However, unlike the categorical approach, the individual approach does not have clear indicators to determine it, and in many cases it is based on experiences of experienced physiotherapists etc. In recent years, with the declining birthrate and aging population, the proportion of elderly people has increased, the number of physiotherapists is insufficient for the number of patients, and it is becoming difficult for inexperienced physiotherapists to devise individual approaches for each patient[2].

Therefore, it is necessary to set indicators of individual approaches, so that all physiotherapists perform appropriate individual approaches and can apply equal quality rehabilitation to all patients. In order to determine this indicator, in this study, we estimate stress of the patient by applying machine learning analysis by neural network(NN) to R-R interval (RRI) of the patient's heart beat obtained by WBAN (Wireless Body Area Network)[3][4].

However, machine learning processing needs big data and a large amount of computational complexity and sending heart rate data via cloud network to AI server computer like Watson for machine learning processing which costs much and causes network delay. So we propose how to reduce computational complexity to enable to calculate by limited processing power in embeded processor of BAN cordinator. Specifically, we aim to reduce it to use NN with preprocessing by wavelet transform and extraction of coefficient of variance of RRI,i.e. CVRR. We evaluated the learning speed, the discrimination rate of the presence or absence of stress, and the computational complexity of proposal system by computer simulation and indicated that the learning efficiency of the NN was increased by preprocessing.

2 Proposal System

2.1 System Model

In this research, we estimate two classes whether or not the patient feels stress. Fig.1. shows the system model of stress estimate by NN with preprocessing. In this system, preprocessing in combination and extracting a part of features beforehand and the calculation complexity for feature extraction in the NN is reduced. Preprocessing is performed based on medical knowledge and we perform extraction of CVRR and wavelet transform. Moreover, we perform pre-learning with NN from only CVRR in parallel with wavelet transform and extract a part of stress features of CVRR beforehand because computational complexity of wavelet transform needs much more complex than that of extraction of CVRR. After pre-learning of CVRR and wavelet transform,we perform main learning with NN. In main learning, we extract of features from both of CVRR and frequency components and estimate stress.

2.2 Preprocessing

It is known that RRI in heartbeat correlates with stress, and it is known that when the patient feels stress, the value of RRI and the magnitude of the variation are smaller than usual. Therefore, CVRR which is the variation coefficient of RRI is derived from the following formula[5]. If this value is small, it can be estimated

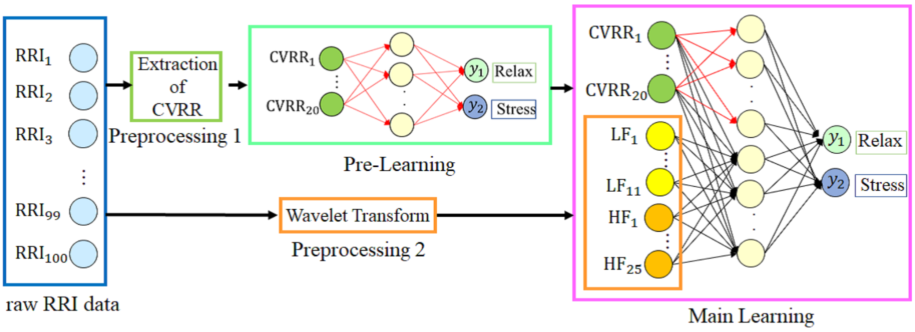

Fig. 1. System Model of Stress Estimate

that the patient feels stress.

$$\mathrm{CVRR} = \frac{\mathrm{SDRR} * 100}{\mathrm{mRR}} \tag{1}$$

mRR and SDRR means mean RRI and standard deviation of RRI respectively.

In addition, we extract frequency components that can be divided into High Frequency(HF) from 0.15 Hz to 0.40 Hz and Low Frequency(LF) from 0.04 Hz to 0.15 Hz. The effects of parasympathetic and sympathetic nerves are reflected in HF and LF, respectively. Furthermore, it is known that respiration is related to HF and blood pressure fluctuation is correlated with LF. In this research, we extract frequency component by performing wavelet transform using Morlet wavelet[6].

2.3 Pre-Learning

Pre-learning is performed with three-layer NN that inputs CVRR to the input layer and performs two class estimation of "relax" or "stress" in the output layer. After learning of this NN, stress features of CVRR can be extracted in the hidden layer and we use the obtained weight and bias parameters in the main learning.

2.4 Main Learning

In main learning, we use three-layer NN that inputs CVRR and frequency components of RRI and performs two class estimation in the output layer. Stress features from only CVRR are extracted in the first group, and stress features from both of CVRR and frequency components are extracted in the other group. Features from only CVRR are extracted in pre-learning, so weight of nodes between neurons to which CVRR is input and neurons neurons with features from only CVRR (red nodes of main learning NN in Fig.1) are not updated. In main learning, NN learns to extract features from both of CVRR between input layers and hidden layer and frequency components and estimate stress from these features between hidden layer and output layer.

3 Performance Evaluation

In this research, we performed following two computer simulations and evaluated performance of accuracy, learning speed and computational complexity of proposal system. The computational complexity was evaluated by the number of multiplications.

- Comparison of performance of NN of stress estimate by type of preprocessing
- Comparison of performance of NN with or without pre-learning on CVRR

3.1 Simulation Model and Parameters

Table 1. shows parameters of NN of main learning used in simulation. Dummy data of RRI generated using normal distribution was used to guarantee reproducibility.

Table 1. Simulation Parameters

number of input neurons	56
number of hidden neurons	30
number of output neurons	2
batch size	20
number of epoch	1200
η : learning rate	0.01
RRI signal size	100
number of training data	200
number of test data	10000
activation function(hidden layer)	ReLU
activation function(output layer)	softmax
loss function	crossentropy
optimizer	SGD

In first simulation, we compared performance of NN by type of preprocessing. The type of preprocessing comapared are without preprocessing(input RRI data), only extraction of CVRR, only extraction components and both of extraction of CVRR and frequency components(Proposal). In CVRR extraction, RRI was time-divided into 20 and CVRR was obtained for each data. In the extraction of frequency components, we performed wavelet transform using 36 wavelets with fixed translational value and scales from 0.04 to 0.40 every 0.01. Pre-learning is not performed in this simulation.

In second simulation, we compared performance of NN with or without pre-learning on CVRR. In the case without pre-learning, the NN same to first simulation with preprocessing both of extraction of CVRR and frequency components is used. In the case with pre-learning, the NN of pre-learning has 20 input neurons for CVRR, 10 hidden neurons and other parameters same to the NN of main learning without pre-learning. The NN of main learning with pre-learning has same parameters without pre-learning. Preprocessing same to the case without pre-learning is performed. However, ten of the hidden layer neurons are connected only with neurons of the input layer to which CVRR is input. Also, the bias of these neurons and weights between these hidden neurons and input neurons are not updated.

3.2 Results

Table 3. shows accuracy by type of preprocessing in first simulation. Fig 2 shows learning curves for comparison of learning speed. From these results, preprocessing of extraction of CVRR and frequency components improve learning efficiency. However, in the case with preprocessing of only extraction of frequency components,the performance is worse than in the case without preprocessing. This indicates that both of CVRR and frequency components can be used as a feature of stress but CVRR is more important feature than frequency component. Table **??**. shows number of multiplication for comparison of computational complexity. From this table, preprocessing, especially wavelet transform requires a lot of calculation. However, calculation complexity of learning reduce because the dimension of the data input to the NN becomes smaller and the number of parameters to be updated decreases by preprocessing. Therefore, the calculation complexity of this system with preprocessing is less complex than that of this system without processing.

Table 5., Fig 3., Table 4 shows learning curve, accuracy, amount of multiplication in second simulation, respectively. From 3 and Table 5, it turns out that the initial value of crossentropy is reduced and learning speed improved by pre-learning. From Table 4., Although the amount of calculation by preliminary learning is required, since the parameters to be updated in the main learning are reduced, the amount of calculation in this learning has been reduced.

Table 2. Comparison of number of multiplication by type of preprocessing

number of multiplication	RRI	CVRR	Frequency	Proposal
preprocessing	0	36,000	180,007,200	180,043,200
learning	2,595,360,000	232,320,000	197,280,000	892,320,000
sum	2,595,360,000	232,356,000	377,287,200	1,072,363,200

Table 3. Comparison of accuracy by type of preprocessing

	RRI	CVRR	Frequancy	Proposal
accuracy[%]	81.131	89.664	68.5805	93.41

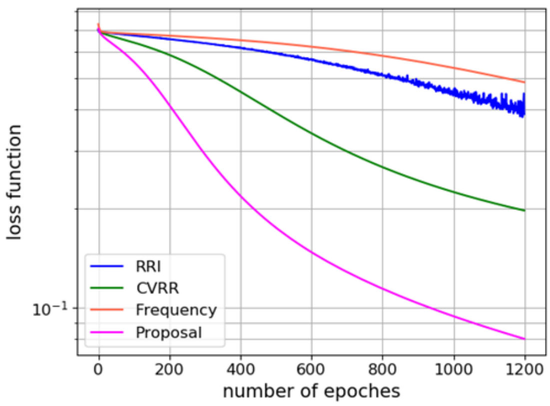

Fig. 2. Comparison of learning speed by type of preprocessing

Table 4. Comparison of number of multiplication with or without pre-learning

number of multiplication	without pre-learning	with pre-learning
pre-learning	—	232,320,000
main learning	892,320,000	538,080,000
sum	892,320,000	770,400,000

Table 5. Comparison of accuracy with or without pre-learning

	without pre-learning	with pre-learning
accuracy[%]	93.41	90.77

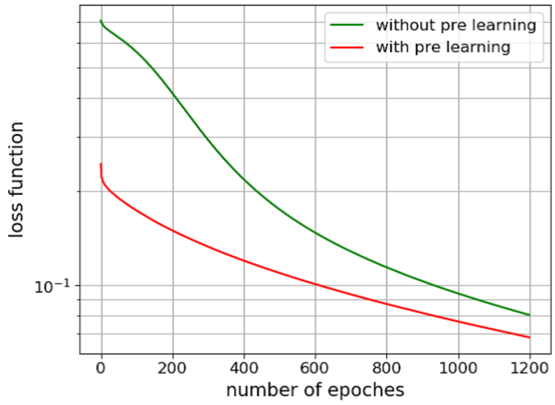

Fig. 3. Comparison of learning speed with or without pre-learning

4 Conclusion

In this research, we proposed the stress estimate system by NN with preprocessing and pre-learning. We confirmed preprocessing and pre-learning can improve performance of NN of stress estimate because these processing can extract a part of stress features beforehand. In the near future, we will consider multi-class stress classification model.

References

1. Maclean, Niall, and Pandora Pound. "A critical review of the concept of patient motivation in the literature on physical rehabilitation." Social science & medicine (2000).
2. Lunenfeld, Bruno. "An aging world-demographics and challenges." (2008)
3. Ali, Mouhannad, et al. "Emotion Recognition Involving Physiological and Speech Signals: A Comprehensive Review." Recent Advances in Nonlinear Dynamics and Synchronization. Springer, Cham, 2018. 287-302.
4. Barakah, Deena M., and Muhammad Ammad-uddin. "A survey of challenges and applications of wireless body area network (WBAN) and role of a virtual doctor server in existing architecture." Intelligent Systems, Modelling and Simulation (ISMS), 2012 Third International Conference on. IEEE, 2012.
5. Cernat, Roxana Al, et al. "Stress influence on drivers identified by monitoring galvanic skin resistance and heart rate variability." E-Health and Bioengineering Conference (EHB), 2017. IEEE, 2017.
6. Ivanov, Plamen Ch, et al. "Scaling behaviour of heartbeat intervals obtained by wavelet-based time-series analysis." Nature 383.6598 (1996): 323.