Project: IEEE P802.15 Working Group for Wireless Personal Area Networks (WPANs)

Submission Title: [Learning and Recognition with Neural Network of Heart Beats Sensed by WBAN for Patient Stress Estimate for Rehabilitation]

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Abstract: [A use case of dependable wireless body area network(WBAN) for learning and recognition of patient stress with machine learning is introduced.]

Purpose: [information]

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

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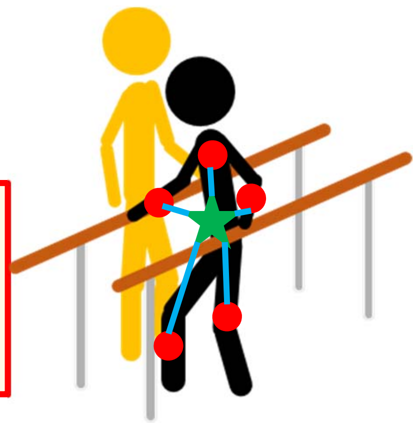
Agenda

1. Introduction : motivation, system model, aim of the research
2. Conventional Method : deep learning as calculation complexity method
3. Basic Proposal Method
   : Basic Proposal Method with Pre-Learning
4. Modified Proposal Method
   :less calculation complexity method by Neural Network with preprocessing
5. Conclusion

1.1 Motivation

- Patients' motivation greatly affects the output of rehabilitation
- To improve efficiency of Rehabilitation, the comfortable environment that patients have no stress is needed
- The therapists should give proper care to patients so that the patients can train with high motivation without stress
- The therapist's ability to estimate stress depends on each experience and there is no common standard
- All therapists can not make the same judgement for stress estimation



Stress estimate in real time using vital signals obtained from WBAN

RRI Heartbeat information from ECG is used in this research.

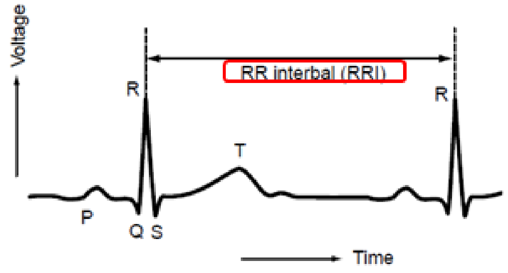
1.2 Aim of this Study

1. Improving efficiency of Rehabilitation
2. Assisting therapists who care for patients during rehabilitation
3. Setting common criteria so that all therapists can estimate patient stress as well
4. Generating real-time stress estimation model by machine learning method
5. In order to estimate patient's stress in real-time, we propose less calculation complexity method

Features in heartbeat regarding stress

RRI (R-R interval)

Time interval of R wave in ECG.
It reflects variation of autonomic nerves correlated with emotion.



CVRR (Coefficient of Variance of RRI)

Index of variance of RRI
CVRR is smaller when the patient feel stress

$$CVRR = \frac{SDRR * 100}{mRR}$$

SDRR: standard deviation of RRI
mRR: mean RRI

Frequency

Frequency component in RRI reflects impact of other biological information.

0.04~0.15Hz(LF : Low Frequency)

→ Blood pressure control system

0.15~0.40Hz(HF : High Frequency)

→ RSA : Respiratory Sinus Arrhythmia

1.3 System Model

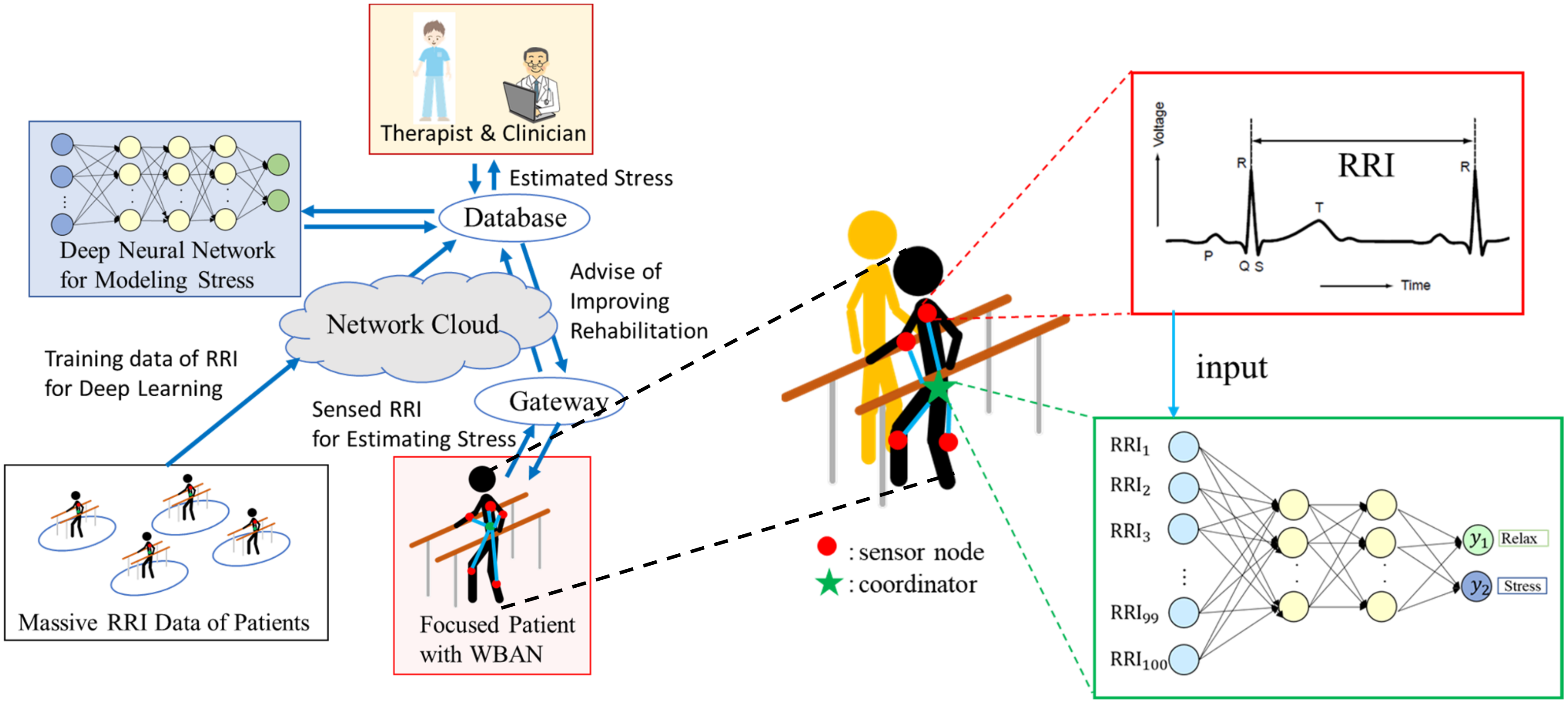


Fig. 1 Entire System for stress estimation

1.4 NN for Stress Estimation

1. RRI data are preprocessed before input to Neural Network (NN)

2. Pre-training is performed with many RRI data from many patients

3. Obtained weights with Pre-training is used as the initial weights of NN for specific patients

4. Part of these weights (Frozen layers) are not updated and hold features extracted with Pre-training

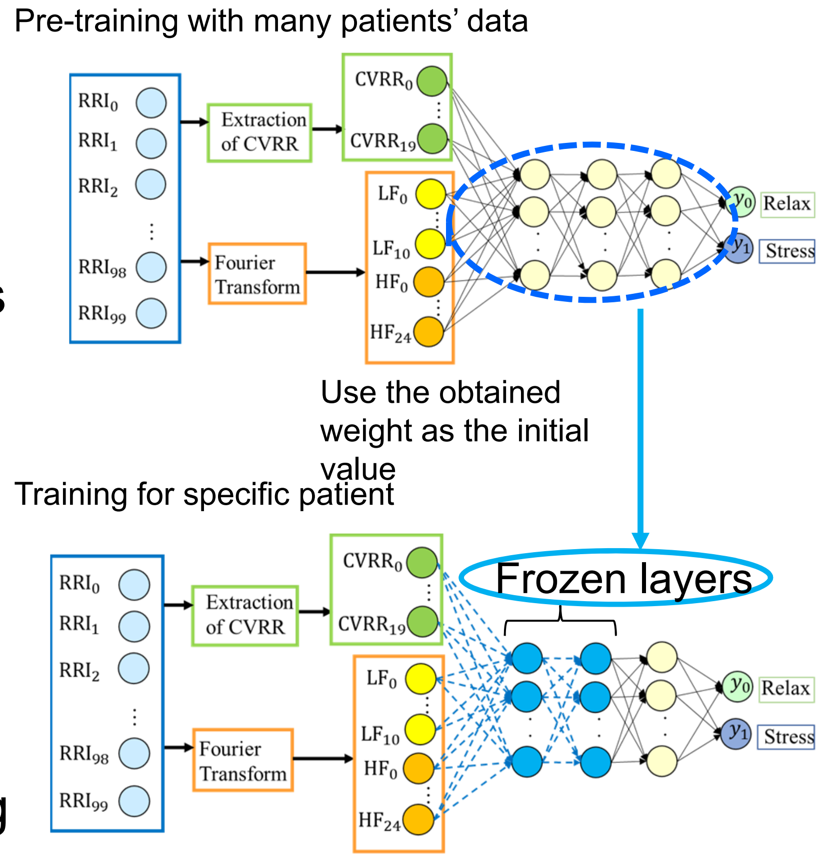


Fig. 2 NN architecture in the simulation

1.5 Proposal of this Study

When computing machine learning with the processor in the WBAN coordinator,

Problem

Machine learning (especially deep learning) requires long time to learn and estimate because of calculation complexity

Aim of the research

- Reduction of calculation complexity for neural network

In my Proposal method,

1. In advance, extract features relating to stress which are known medically
2. Extract the remaining features with neural network
3. This eliminates the need for many hidden layer of neural network.

2.1 Feature Extraction in Neural Network

- The features of the input data is extracted in the unit of the hidden layer
- More features can be extracted as the number of units in the hidden layer is increased
- Finer features can be extracted as the number of the hidden layer is increased
- The number of parameters and calculation complexity increase as the number of units in the neural network increases.
- It is unknown what the extracted features in the hidden layer specifically mean

【Proposal】 Extract necessary features reliably in advance

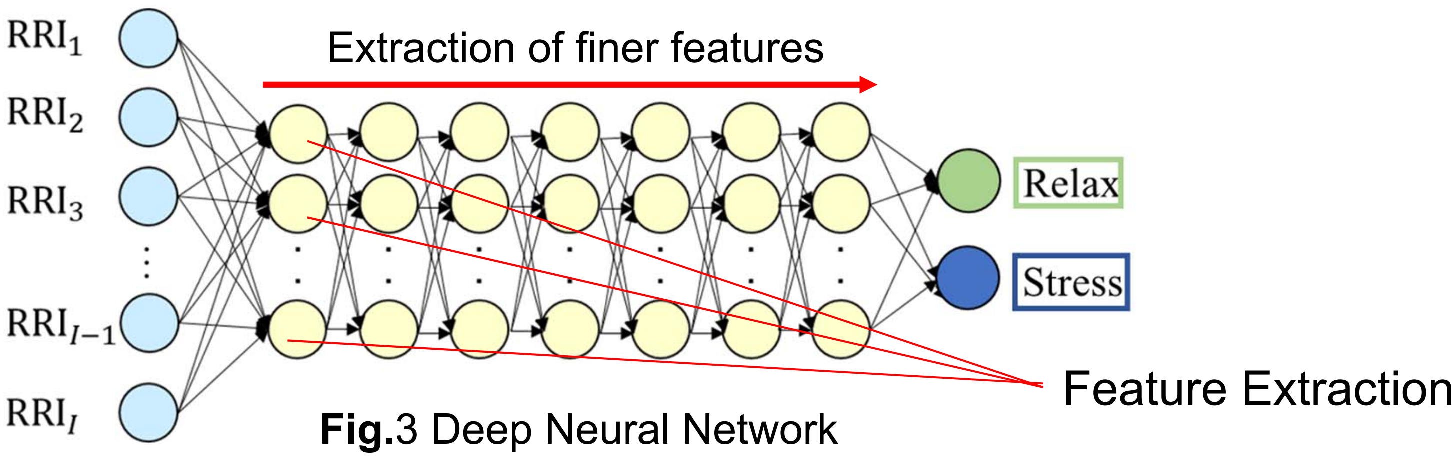
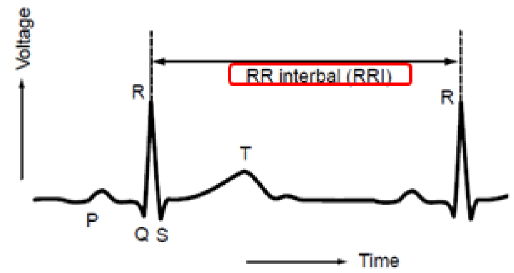


Fig.3 Deep Neural Network

2.2 Features in heartbeat regarding stress

RRI (R-R interval)

Time interval of R wave in ECG.
It reflects variation of autonomic nerves correlated with emotion.



CVRR (Coefficient of Variance of RRI)

Index of variance of RRI
CVRR is smaller when the patient feel stress

$$CVRR = \frac{SDRR * 100}{mRR}$$

SDRR: standard deviation of RRI
mRR: mean RRI

Frequency

Frequency component in RRI reflects impact of other biological information[4].

0.04~0.15Hz(LF : Low Frequency)

→ Blood pressure control system

0.15~0.40Hz(HF : High Frequency)

→ RSA : Respiratory Sinus Arrhythmia

3.1 Preprocessing

- In this research, RRI is input to the neural network as heart beat information.
- In preprocessing, RRI is translated to CVRR and frequency components.
- These feature extraction do not require iterative calculation of weight correction

CVRR (Coefficient of Variance of RRI)

CVRR is derived from RRI by the following formula

$$\mathrm{CVRR} = \frac{\mathrm{SDRR} \times 100}{\mathrm{mRR}}$$

SDRR: standard deviation of RRI

mRR : mean RRI

Frequency

Wavelet transform is performed for extraction of frequency components.

Wavelet transform：Effective time frequency analysis for unsteady signals like biosignals

x(t): RRI signal

$\psi_{a,b}(t)$: wavelet

$$\mathcal{W}_{\psi}[x(t)] = T(a,b) = \int_{-\infty}^{\infty} x(t)\psi_{a,b}^{*}(t)dt$$

3.2 Proposal System

Proposal

Preprocessing is performed instead of multilayered Neural Network.
It is possible to reliably extract useful features while reducing calculation complexity for learning

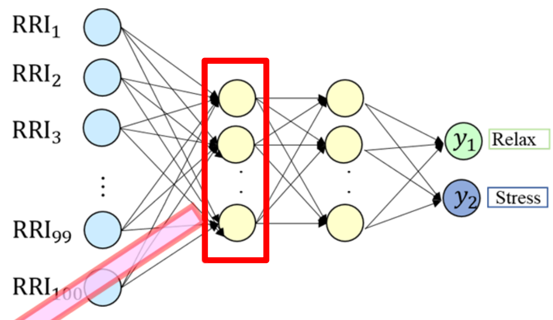


Fig.4 Multilayered Neural Network

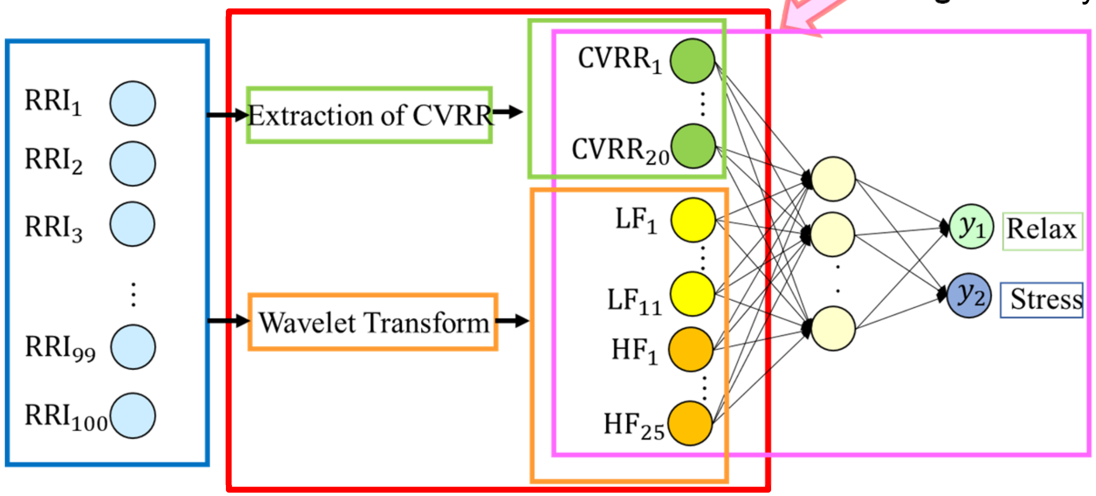


Fig.5 proposal system

3.2 Simulation regarding preprocessing

Comparison of the following performances of neural network depending on presence or absence of preprocessing and the type of preprocessing(only CVRR, only wavelet transform, CVRR and wavelet transform)

- learning speed
- accuracy
- calculation complexity
  (number of multiplication)

In order to ensure reproducibility, we used artificial RRI data with label('relax' or 'stress') in this simulation.

Table. 1 simulation parameters

input neurons	56
hidden neurons	30
hidden layer	1
output neuron	2
activation function(hidden layer)	ReLU
activation function(output layer)	softmax
loss function	crossentropy
learning rate	0.01
optimizer	SGD
batch size	20
max epoch	1200

3.3 Results

Table. 2 comparison of calculation complexity

multiplication	RRI	Proposal
Preprocessing	0	180,043,200
Learning	2,595,360,000	892,320,000
total	2,595,360,000	1,072,363,200

Table. 3 comparison of accuracy

	RRI	CVRR	Frequency	Proposal
Accuracy[%]	81.13	89.66	68.5805	93.41

- Preprocessing reduced calculation complexity of learning
- Accuracy is improved by preprocessing
- Preprocessing of only extraction of CVRR also improve accuracy.
- Preprocessing of only wavelet transform decline accuracy
- CVRR is more important feature than frequency component

3.3 Results

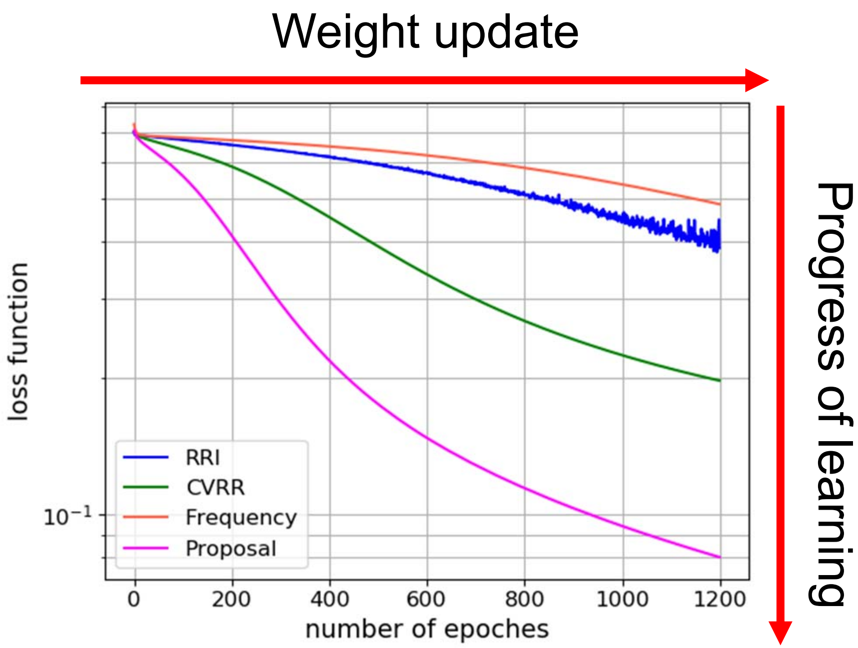


Fig. 6 comparison of learning speed

- Preprocessing of only extraction of CVRR improve learning speed
- Preprocessing of only wavelet transform decline learning speed
- CVRR is more important feature
- Combination of two types of preprocessing more than CVRR alone

- Frequency components are necessary, but CVRR is more dominant feature and important.

4.1 Pre-Learning

- Pre-Learning is introduced to proposal method in order to extract feature of CVRR reliably
- Weight obtained in Pre-Learning is used for Main Learning
- In Main Learning, Feature from both of CVRR and frequency components are extracted
- Weight of Red node is not updated in order to protect features obtained in Pre-Learning

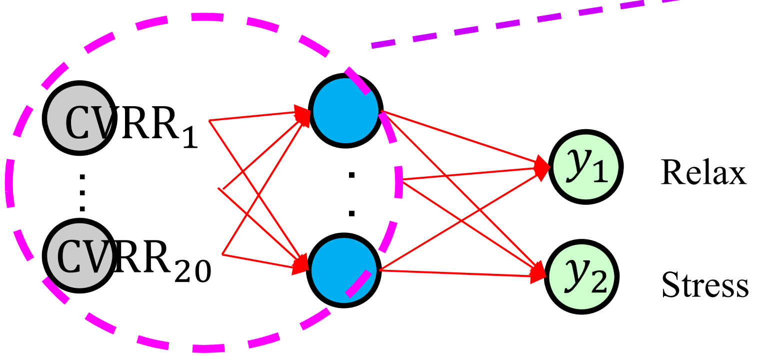


Fig.7 Pre-Learning

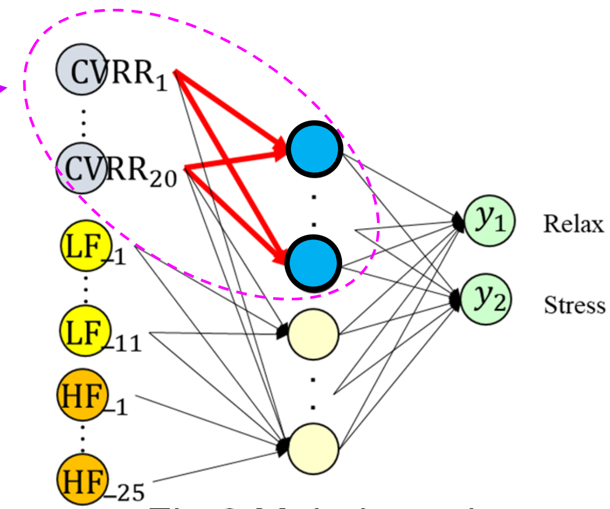


Fig.8 Main Learning

4.1 Modified Proposal System

1. Preprocessing is performed to RRI, and CVRR and frequency component is extracted
2. Pre-Learning is performed with CVRR and features are extracted from CVRR
3. Main Learning is performed and features are extracted from both of CVRR and frequency components

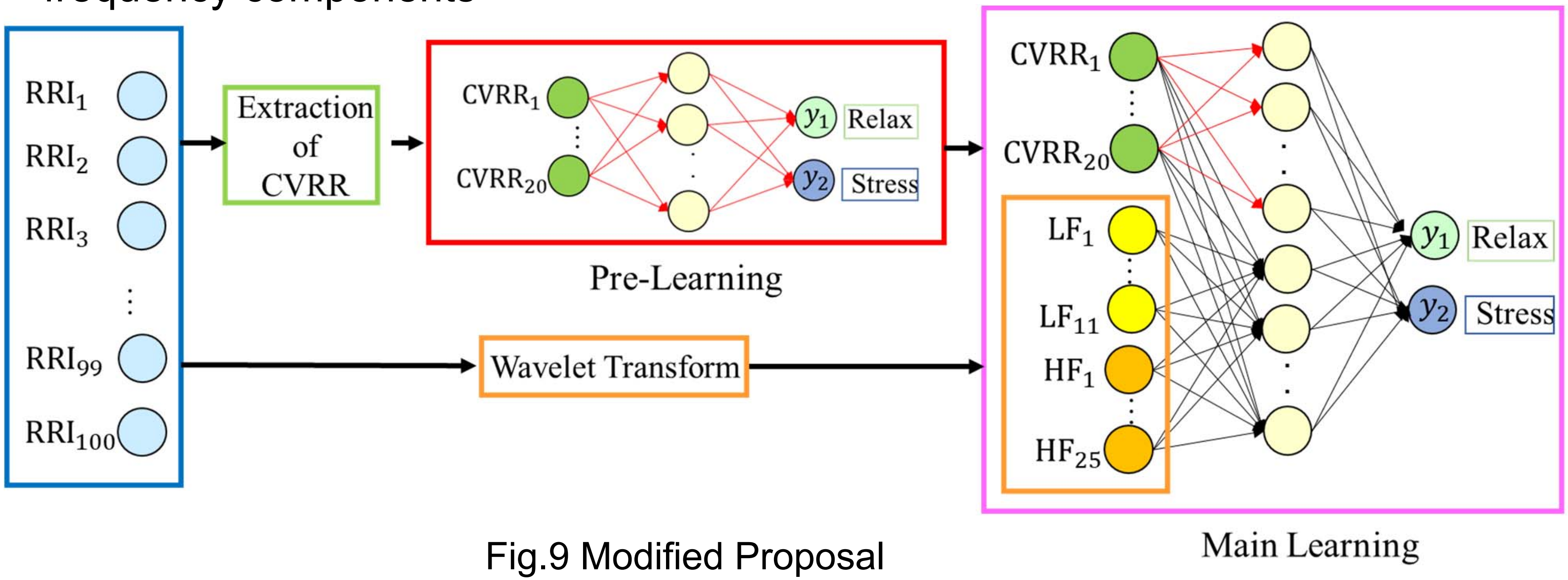


Fig.9 Modified Proposal System

4.2 Simulation regarding Pre-Learning

Comparison of the following performances of neural network with preprocessing depending on presence or absence of Pre-Learning

- learning speed
- accuracy
- calculation complexity
  (number of multiplication)

- Table. 4 shows simulation parameters of Pre-Learning.
- Parameters of Main-Learning is same to the simulation just before.

Table. 4 simulation parameters of Pre-Learning

input neurons	**20**
hidden neurons	**10**
hidden layer	**1**
output neuron	**2**
activation function(hidden layer)	**ReLU**
activation function(output layer)	**Softmax**
loss function	**Crossentropy**
learning rate	**0.01**
optimizer	**SGD**
batch size	**20**
max epoch	**1200**

4.3 Results

Table. 5 comparison of calculation complexity

multiplication	without pre learning	with pre learning
Pre-Learning	0	232,320,000
Main-Learning	892,320,000	538,080,000
Total	892,320,000	770,400,000

Table. 6 comparison of accuracy

	without pre learning	with pre learning
Accuracy[%]	93.41	90.77

- Number of features is reduced in main learning by Pre-Learning
- Pre-Learning reduced calculation complexity

- Accuracy is declined by Pre-Learning
- It is considered that overfitting occurred because the method of extracting features was overly restricted.

4.3 Results

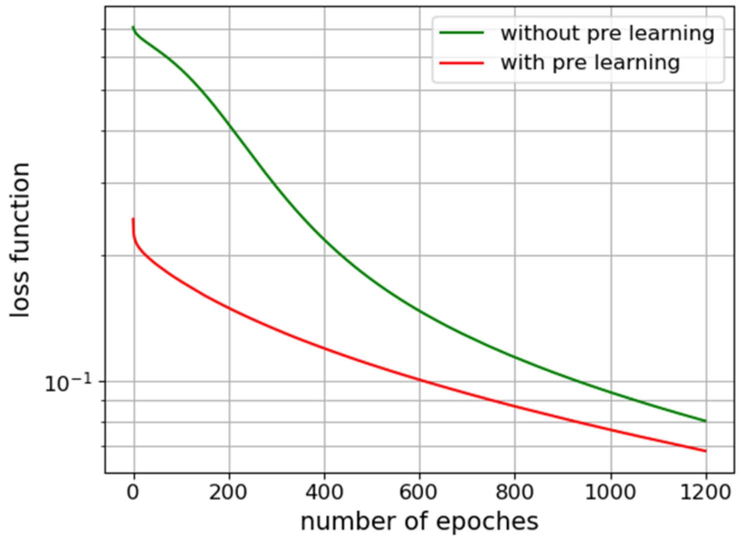


Fig. 10 comparison of learning speed (with pre-learning vs without pre-learning)

- Pre-Learning improved learning speed and reduced calculation complexity
- High learning speed is an important factor in estimating in real time.
- However, overfitting is occurred so we should consider method for extract better features.

4.4 Summary of Simulation

We compared 4 conditions

condition	1	2	3	4
Preprocessing		✓	✓	✓
Pre-training			✓	✓
Frozen weights				✓

- Preprocessing and Pre-training reduced calculation complexity
- Frozen weights reduced over fitting

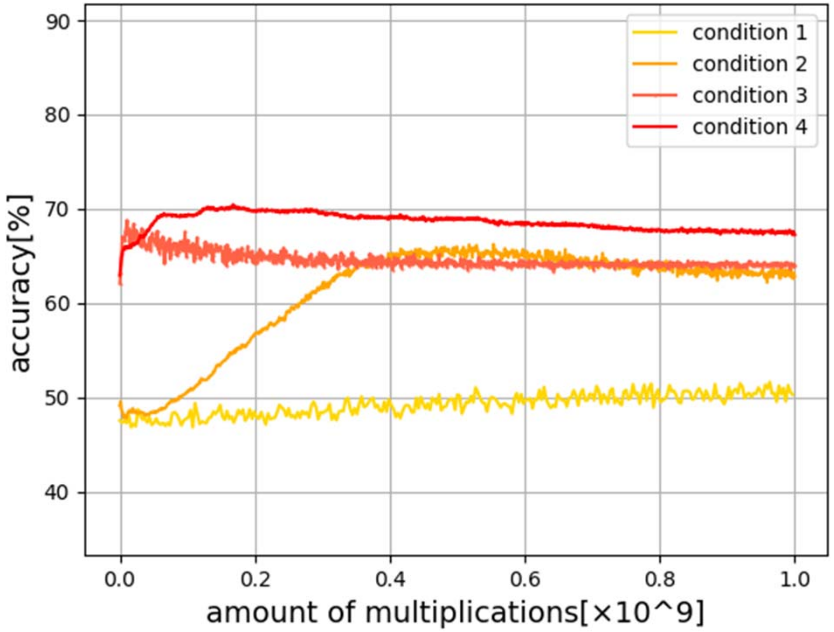


Fig. 3 Amount of multiplication versus Accuracy

Table. 1 The amount of multiplication

condition	1	2	3	4
1000 epoch	33.8×10^9	12.1×10^9	12.1×10^9	6.1×10^9

5. Decision for number of hidden units

- We should decide the number of hidden units and layers in designing Neural Network
- In many cases, many units and many hidden layers are installed for no reason.
- In this research, It is important to prevent an increase in calculation complexity
- We decide the number of hidden units based on accuracy and calculation complexity

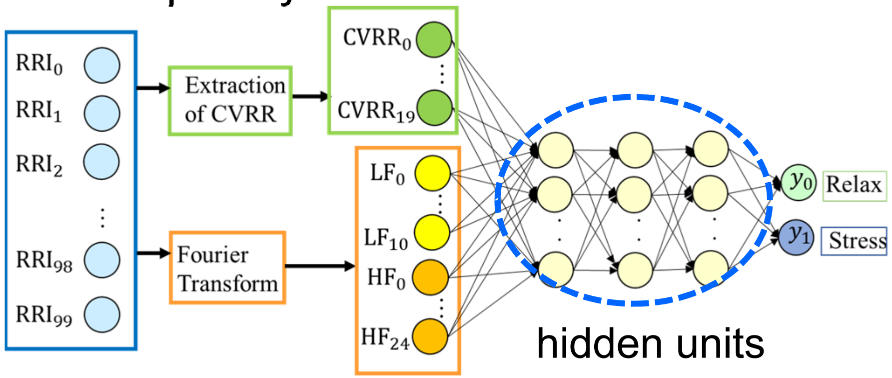


Table. 2 The number of hidden units

Num of Hidden units	small	appropriate	large
Accuracy	low	high	middle
Calculation complexity	Small		Large

5.1 Simulation. 1

1. Evaluation for accuracy of 3 layers NN with limited number of multiplication

- Grid search for cases with 1 to 100 hidden units.
- Determine the appropriate number of hidden units to guarantee sufficient accuracy with less calculation complexity

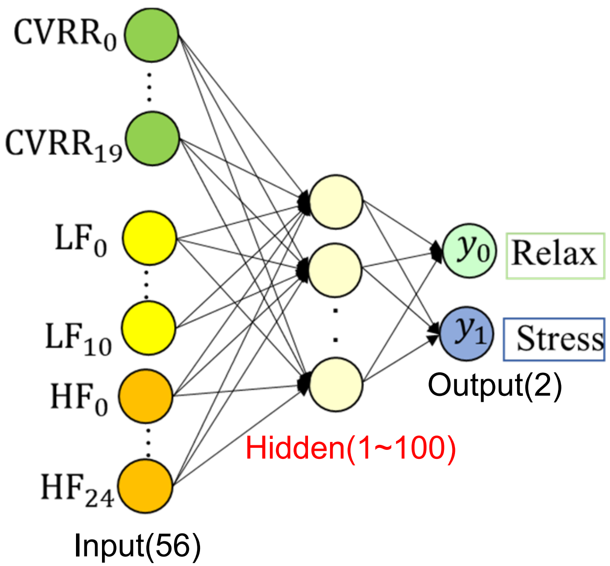


Fig. 4 NN for Simulation. 1

Table. 3 Parameters for Simulation. 1

input units	56
hidden units	1,10,20, … , 100
hidden layer	1
output units	2
activation function(hidden layer)	ReLU
activation function(output layer)	softmax
loss function	crossentropy
learning rate	0.01
Optimizer	SGD
batch size	20
number of multiplication	~1.0×10^9

5.1 Result of Simulation. 1

- From Fig.6, 40 and 50 hidden units shows best accuracy
- Need more Grid Search around 40 to 50 hidden units
- Temporarily use 40 hidden units as the appropriate number of units for s

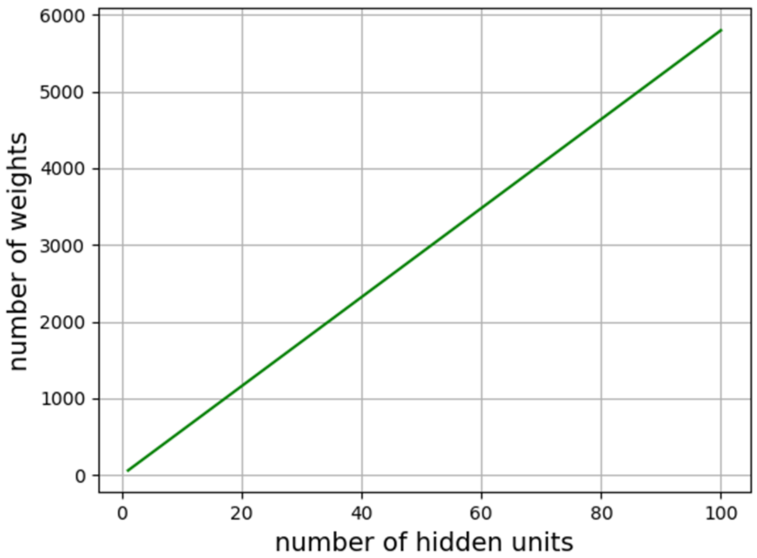


Fig. 5 Number of weights of NN

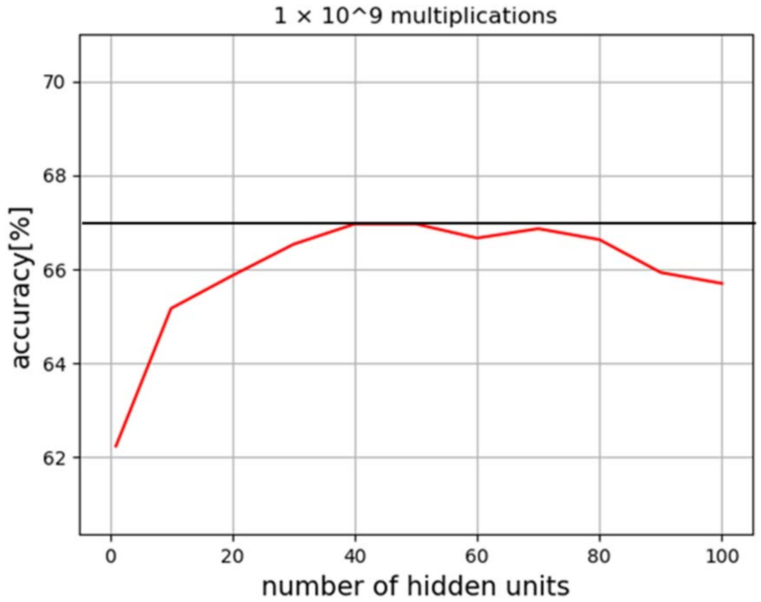


Fig. 6 Accuracy with 1.0×10^9 multiplications

5.2 Simulation. 2

2. Evaluation for accuracy of NN which has total 40 hidden units

- Comparison for cases with 1, 2, 4, 8, 10 hidden layers
- With limited number of multiplications
- All hidden layers has same number of hidden units
- Determine the appropriate number of hidden layers to guarantee sufficient accuracy

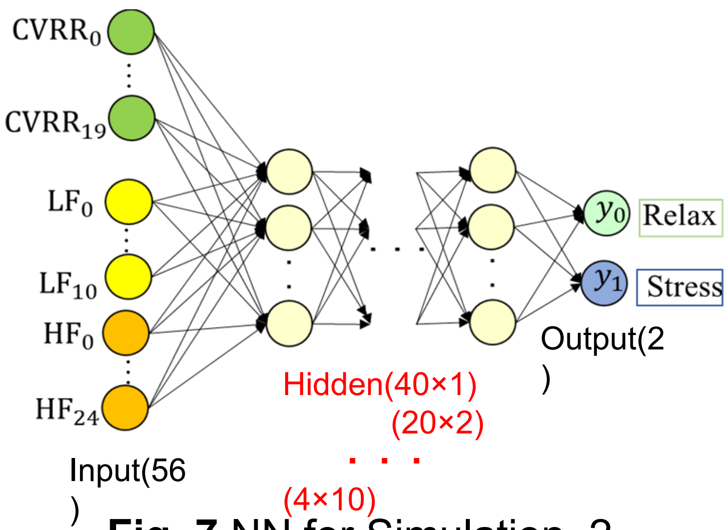


Fig. 7 NN for Simulation. 2

Table. 4 Parameters for Simulation. 2

input units	56
hidden units	40, 20, 10, 5, 4
hidden layer	1, 2, 4, 8, 10
output units	2
activation function(hidden layer)	ReLU
activation function(output layer)	softmax
loss function	crossentropy
learning rate	0.01
Optimizer	SGD
batch size	20
number of multiplication	$\sim 1.0\times 10^9$

5.2 Result of Simulation. 2

- From Fig.8, the more hidden layers has less number of multiplications for 1 epoch in the case of same total number of hidden units
- From Fig.9, the more hidden layers shows lower accuracy

Fig. 8 Number of weights of NN

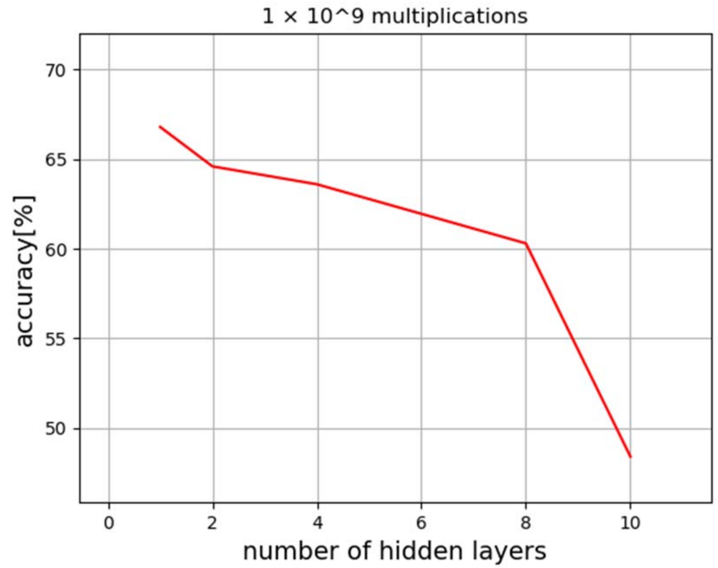


Fig. 9 Accuracy with 1.0×10^{9} multiplications

5.3 Simulation. 3

2. Evaluation for accuracy of NN which has around 2000 weights

- Comparison for cases from 1 to 7 hidden layers
- With limited number of multiplications
- All hidden layers has same number of hidden units
- Determine the appropriate number of hidden layers to guarantee sufficient accuracy

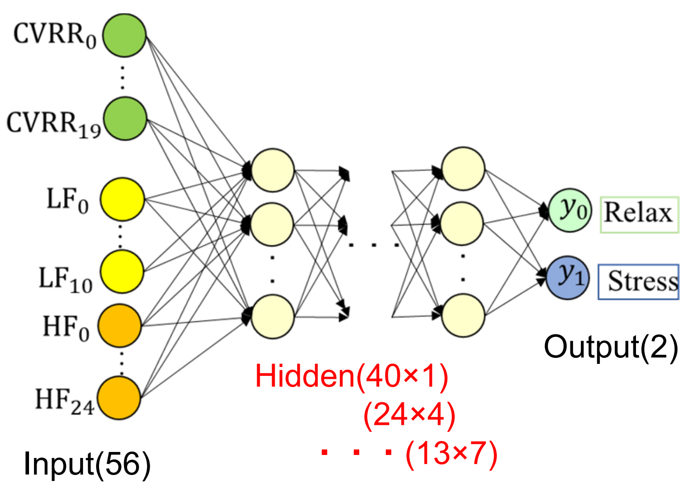


Fig. 10 NN for Simulation. 3

Table. 5 Parameters for Simulation. 3

input units	56
hidden units	40, 24, 19, 17, 15, 14, 13
hidden layer	1, 2, …, 7
output units	2
activation function(hidden layer)	ReLU
activation function(output layer)	softmax
loss function	crossentropy
learning rate	0.01
Optimizer	SGD
batch size	20
number of multiplication	~1.0×10^9

5.3 Result of Simulation. 3

- From Fig.11 and 12, accuracy is almost equal when the number of weights of NN are close
- We confirm accuracy with the same number of calculation depends on the number of weights rather than the number of units in the hidden layer.

Fig. 11 Number of weights of NN

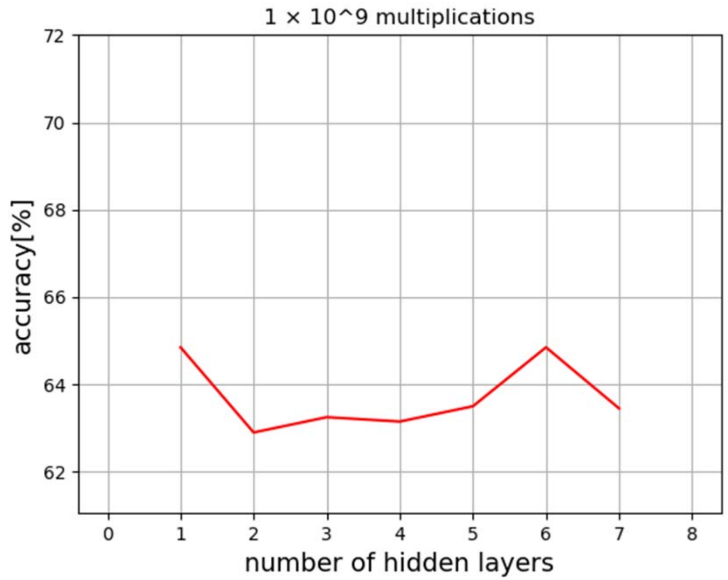


Fig. 12 Accuracy with 1.0×10^{9} multiplications

6. Conclusion and Future work

Conclusion

- We try to decide appropriate number of hidden units so that accuracy with the case of the same number of calculation improves
- From results, we confirmed accuracy with the same number of calculation depends on the number of weights rather than the number of hidden units or hidden layer.

Future Work

- Decision for appropriate number of weights of NN
- Decision for appropriate number of hidden layers and units in each layer

5. Conclusion

Conclusion

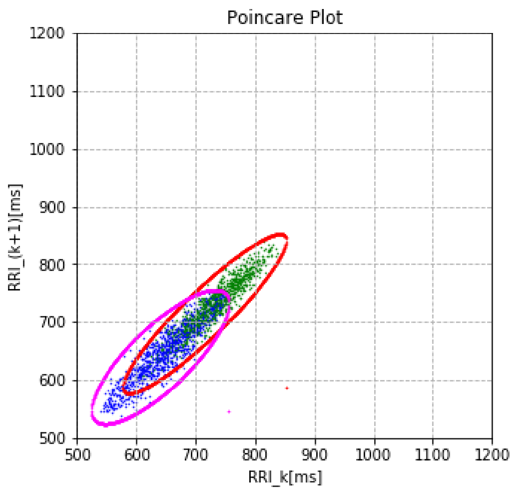
- We proposed a method to perform learning by neural network after feature extraction by preprocessing and Pre-Learning to reduce calculation amount
- Preprocessing and Pre-Learning improved learning speed and reduced calculation complexity
- Pre-Learning declined accuracy because of overfitting
- We should consider method for extract better features.]
- We derived appropriate number of hidden units so that accuracy with the case of the same number of calculation improves
- From results, we confirmed accuracy with the same number of calculation depends on the number of weights rather than the number of hidden units or hidden layer.

Future Work

- Decision for appropriate number of weights of NN
- Decision for appropriate number of hidden layers and units in each layer

Thank you for your attention

Appendix 1. Artificial RRI signal



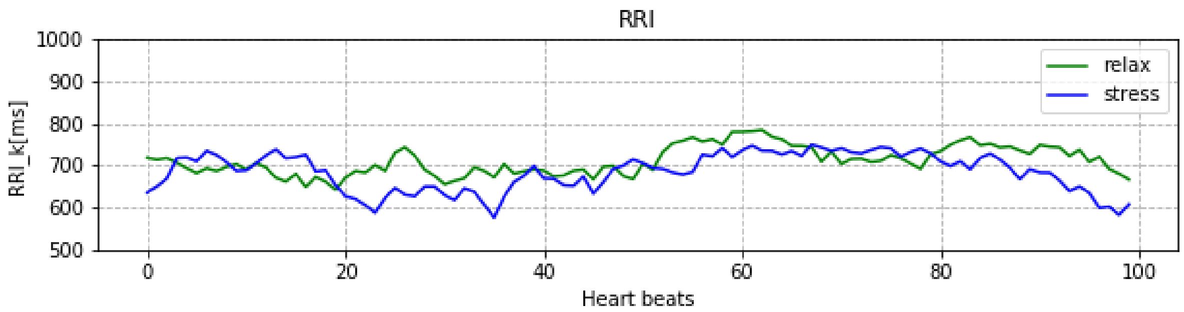


Fig 11 Artificial RRI signal