Proposal of Exercise Evaluation Method of Musculoskeletal Disorder Sufferers by Using Feed-Forward Neural Network

Mari Takabatake, Chihiro Ikuta, Shuichi Aono, Yoko Uwate and Yoshifumi Nishio
Dept. of Electrical and Electronic Engineering, Tokushima University,
2-1 Minami-Josanjima,Tokushima, 770-8506 JAPAN
Email: {mari, ikuta, uwate, nishio}@ee.tokushima-u.ac.jp
Multidisciplinary Pain Center, Aichi Medical University
1-1 Yazako-Karimata, Nagakute, Aichi, 480-1195, Japan
Email: aono@aichi-med-u.ac.jp

***Abstract*—A quantification of pain is not yet discovered. The pain sometimes informs us about something that threatens a person's life. To maintain life, it is very important that we know the pain. The study of musculoskeletal pain is later than study of pain of the other parts. In this study, we evaluate a momentum and distribute the health condition by using the feed-forward neural network (FNN). The FNN needs to optimize parameters for the evaluation. We tune the parameters and show the performance of the evaluation in each parameter. Finally, we evaluate the unlearned data by using the tuned FNN. And, the FNN evaluate the unlearned data.**

I. Introduction

The pain sometimes informs us about something that threatens a person's life. To maintain life, it is very important to know the pain. The study of musculoskeletal pain is later than study of pain of the other parts[1]. Musculoskeletal disorder sufferers cannot move enough even a simple motion. They limit exercise unconsciously because of pain. Furthermore, it leads to disuse muscle atrophy. Therefor, we consider that an evaluation of their health condition is important for increasing motivation of treatment of disease. Furthermore, the evaluation can be usable for an index to express condition of the disorder sufferers.

In this study, we evaluate the health condition by using an acceleration sensor of iPhone and a FNN[2]. [1] We obtain the acceleration time-series data of human motions by iPhone. We give this data to the FNN, and the FNN learns the classification of the evaluation of the motion by a back propagation algorithm[3]. We show the FNN model in Fig. 1. By this learning, we show that the FNN obtains an ability of the evaluation of the health condition.

II. Proposed method

In the measurement, we use a sensor monitor of the iPhone application. Firstly, the examinee puts the iPhone in the right pocket of pants. Secondly, we obtain the acceleration time-series data of jump exercize in the radio exercises. We use

[1]We have already reported this method in Proc. of SJCIEE, 2014

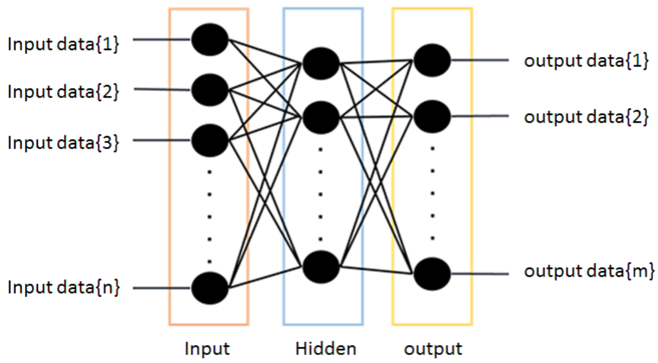

Fig. 1. FNN model.

only a vertical component of acceleration data for the input data. We show an example of the acceleration time-series data in Fig. 2. We prepare 120 acceleration time-series data for the sake of leaning data in three different health conditions (40 health, 40 little pain, 40 intense pain). From the time-series data, we extract only first 30 points whose variations are larger than 0.3. These 30 points are input to the FNN, and the FNN learns the classification of the health conditions. During the learning, different output patterns are given as teacher patterns for different input data.

Namely, for the input data of the health, one of the neurons among output{1}-{40} learns 1 and all the rest learn zero. For the input data of the little pain and the intense pain, only one of the neurons among output{41}-{80} and output{81}-{120} learns 1, respectively. As shown from the Fig. 2, the acceleration time-series data are different each.

III. Simulation

In this study, we use the FNN of three layers and use a sigmoid function to an activation function of the neuron. The

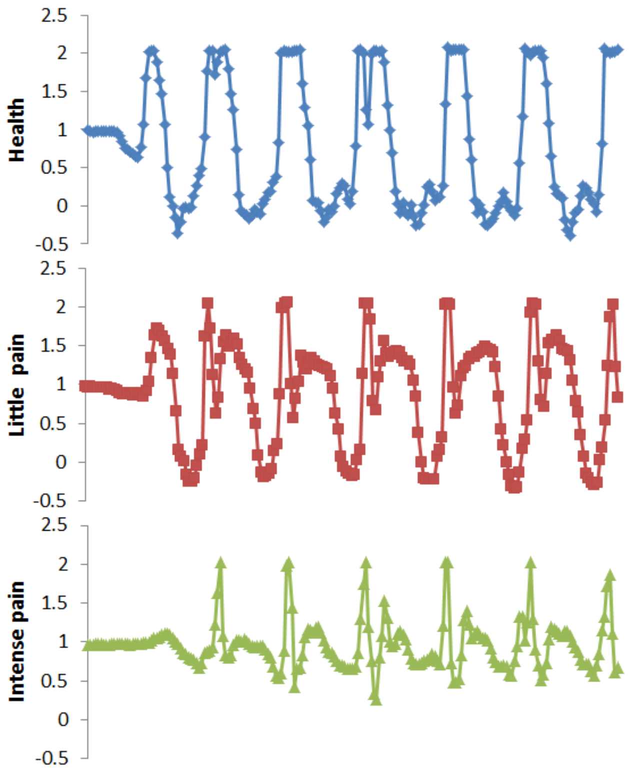

Fig. 2. Acceleration time-series data.

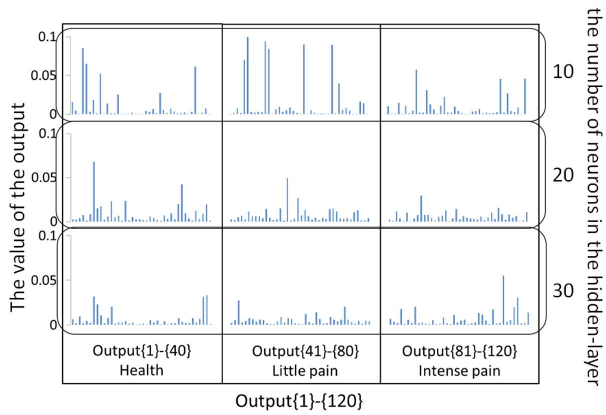

Fig. 3. Result of changing the number of neurons in the hidden-layer.

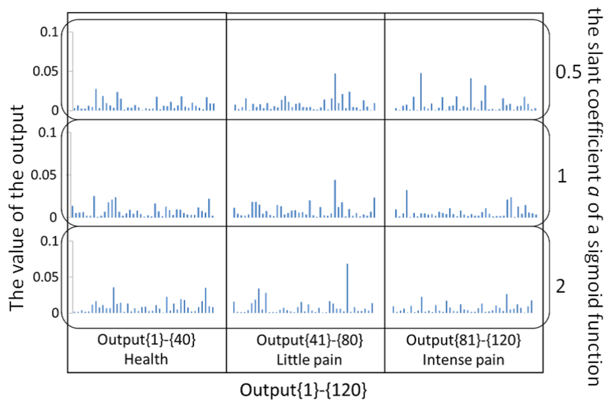

Fig. 4. Result of changing the slant coefficient (a) of a sigmoid function.

sigmoid function is described by Eq. (1)[4].

$$O_k = \frac{1}{1+e^{-ax}}, \tag{1}$$

where O is an output of the neuron, a is a slant coefficient, and x is a net value of the neuron.

A. Parameter setting

We change the number of neurons in the hidden-layer and the slant coefficient (a) of a sigmoid function. Figure 3 and 4 show the output data when the number of neurons in the hidden-layer is changed and when the slant coefficient (a) of a sigmoid function is changed, respectively. The vertical axis of this graph shows a value of the output, and the cross axle expresses a neuron of the output layer.

We evaluate the unlearned data by the value of the output data nearing 1 or 0. In Fig. 3, as the number of neurons in the hidden-layer is increased, the value of the output becomes small. The number of neurons in the hidden-layer at the time of 10, the value of the output is too inconsistent. It shows that the learning is insufficient. The number of neurons in the hidden-layer at the time of 30 or more, the value of the output is too small. It shows that the FNN cannot evaluate the unlearning data by individual difference. In Fig. 4, as the slant coefficient (a) of a sigmoid function is increased, the value of the output becomes small. The slant coefficient (a) of a sigmoid function at the time of 1, 2, or more, the value of the output is too small. it shows that the FNN cannot evaluate the unlearning data by individual difference. From the above, in this study, we decide that the number of neurons in the hidden-layer is 20 and that the slant coefficient (a) of a sigmoid function is 0.5.

B. Health classification of unlearned data

After learning, we input the unlearned data of three different health conditions to the FNN and obtain the response of each neuron output in the output-layer. In Fig. 5, we show the neuron output in the output-layer for the unlearned data of three different health condition.

Figures 5 (a), (b), and (c) show the output data for healthy person, little pain person, and intense pain person, respectively. The horizontal axis of this graph shows output1-output120.

Table 1 shows the maximum of this output in the corresponding health conditions. The true classification should be the health (1, 0, 0), the little pain (0, 1, 0), and the intense pain (0, 0, 1). The maximum of the output for unlearned data shows a similar trend to the true classification.

As shown from Fig. 4 and Table 1, the health conditions of the person are same as expectation at the time of little pain

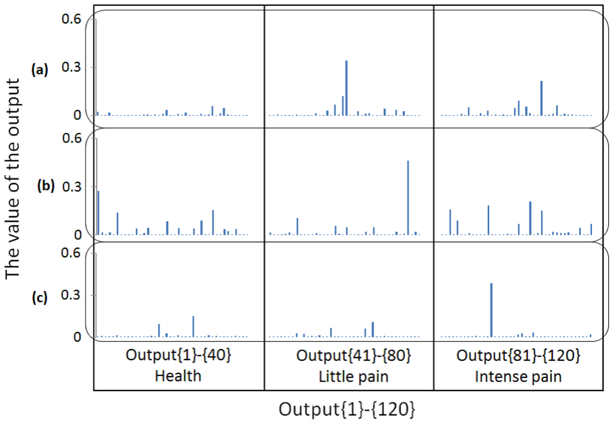

Fig. 5. Neuron outputs in different health conditions' data(1).

TABLE I
OUTPUT OF UNLEARNED DATA(1).

Max. of output	{1}-{40}	{41}-{80}	{81}-{120}
Health	0.059967	0.343105	0.214168
Little pain	0.272177	0.461883	0.208361
Intense pain	0.150053	0.106716	0.386552

and intense pain.

Next, we show the output of the different person in Fig. 6.

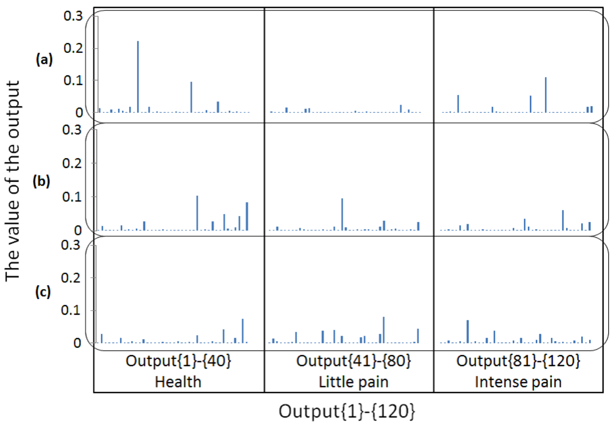

Fig. 6. Neuron outputs in different health conditions' data(2).

TABLE II
OUTPUT OF UNLEARNED DATA(2).

Max. of output	{1}-{40}	{41}-{80}	{81}-{120}
Health	0.222047	0.023339	0.110481
Little pain	0.102815	0.096372	0.059966
Intense pain	0.073592	0.079239	0.070356

As shown from Fig. 6, the health conditions of the person are same as expectation at the time of Health.

IV. CONCLUSION

In this study, we have proposed the evaluation method of the health conditions by using the FNN. We succeeded the evaluation of health conditions in unlearned data. However, the difference between the result of the FNN and the true classification was still large. In the future work, we will increase the number of acceleration time-series data and will find better parameters of the FNN.

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