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Momentum Evaluation of Musculoskeletal Suffers by Using Feed-Forward Neural Network

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1. Introduction

Musculoskeletal suffers cannot move enough even a simple motion. For the suffers, we consider that an evaluation of their health condition is important for increasing motivation of a healing of the disease. In this study, we evaluate the health condition by using an acceleration sensor of iPhone and a feed-forward neural network (FNN) . 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. By this learning, we show that the FNN obtains an ability of the evaluation of the health condition.

2. 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 by jumping with both feet in the radio exercises. We show an example of the acceleration time-series data of the healthy person in Fig. 1.

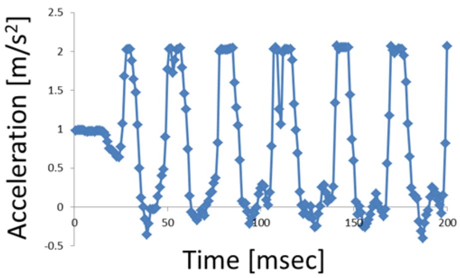

Figure 1: Acceleration time-series data.

We prepare 120 acceleration time-series data for the sake of leaning data in three different health condition (40 health, 40 little pain, 40 intense pain).

From the time-series data, we extract only first 30 points whose variations are larger than 3.0. These 30 points are inputted 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.

3. Simulation

In this study, we use the FNN of three layers and use a sigmoid function to an activation function of the neuron. The sigmoid function is described by Eq. (1).

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

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

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. 2, we show the neuron output in the output-layer for the unlearned data of three different health condition.

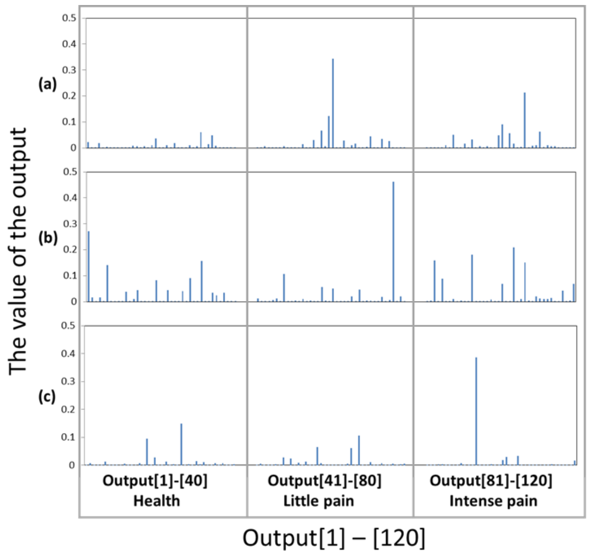

Figure 2: Neuron outputs in different health conditions' data.

The vertical axis of this graph shows a value of the output. Figures 2 (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 output[1]-output[120].

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.

Table 1: output of unlearned data.

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

4. Conclusions

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.