Estimation of Degree of Human Fatigue Score by Defined Data Distance
in Large-Scale Data-Based Online Modeling

Yuriko Hachiya1,2, Masatoshi Ogawa2, Sho Kawanari2, Hideaki Suzuki1 and Harutoshi Ogai2

1 Health Center, University of Occupational and Environmental Health, Japan
1-1 Iseigaoka, Yahatanishi-ku, Kitakyushu, Fukuoka 807-8555, Japan
2 Graduate School of Information, Production and Systems, Waseda University
2-7 Hibikino, Wakamatsu-ku, Kitakyushu, Fukuoka 808-0135, Japan
E-mail: ^hachiya, suzuhye@med.uoeh-u.ac.jp, ^stream@asagi, kawanari@suou, ogai@.waseda.jp

Abstract  It is important to quantify and prevent mental fatigue in order to forestall absence from work and death from overwork. In this study, we used “Large-scale Data-based Online Modeling (LOM)”, one of the local modeling methods based on databases, to reproduce the characteristics of fatigue based on information derived from observation of biomedical signs. The subjects in our study were 10 male university students. After assuming a relaxed seated position for 10 minutes, they performed two repeated sessions of a mental arithmetic task for 30 minutes each session with a 30-minute break. Subjective symptoms of feelings of fatigue score were evaluated on a 10-point scale. We measured several biomedical signs and subjective symptoms of feelings of fatigue score. We propose that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method. We propose a method for determining the reliability of estimating “degree of fatigue” by distance of neighboring data.

Keywords: large-scale data-based online modeling, fatigue, just-in-time modeling, visual display terminal, stepwise method

1. Introduction

It is important to quantify and prevent mental fatigue in order to forestall absence from work and death from overwork. A mathematical model of the phenomenon of fatigue has not been formulated. Because the material causes of fatigue are unknown, the mechanism of fatigue is poorly understood, and there are ramifications of the biological systems in organisms. For that reason, “degree of fatigue” is currently measured by subjective, self-reported symptoms of fatigue.

However, as feelings of fatigue depend on the individual’s judgment, they cannot be understood by a third party. An objective index of fatigue that can be understood by a third party is necessary for making an accurate assessment of workers’ fatigue levels.

In this study, we used “LOM” [1-5], one of the local modeling methods based on databases, to reproduce the characteristics of fatigue based on information derived from observation of biomedical signs.

In a previous paper [6], we reported the scatter diagram of the measured value of the degree of fatigue and the estimated value in 7,453 times by LOM. The correlation coefficient between the measured value of the degree of fatigue and the estimated value was 0.5722 of determined mental fatigue. This was comparatively higher than the correlation coefficient result of Multiple Regression Analysis (0.2850). In a comparison among subjects, the correlation coefficient between the measured value of the degree of fatigue and the estimated value was 0.9157 in subject E. Finally, we showed the difference square of the estimated value of the degree of fatigue and the estimated value data and distance. The estimated value cannot track the measured value. Because sampling data do not have much, the estimated value changed large. After that, when we examine data, we should show the correlation coefficient of the measured value of the degree of fatigue and the estimated value in a time series, rather than a scatter diagram.

After comparing the correlation coefficient of the measured value of the degree of fatigue and the estimated value by the LOM method and the Multiple Regression Analysis method, we suggest that LOM is effective.

2. Fatigue

We discuss the methods of mental fatigue values used in established research: (1) physiological values, (2) metabolic and secretory values, and (3) subjective values. The methods of mental fatigue values used in established research [7, 8] is presented in Table 1.

Group (1) includes pulse wave fluctuation, increase and decrease in a power spectrum of high and low frequencies of heartbeat [9,10], and the rate of electroencephalograph α
waves. We detected stress from them [11-13], but many issues remain unsolved. Because the general notion of fatigue is defined rather vaguely, the mechanism of fatigue cannot be solved, and it is difficult to extract fatigue components from biological signals; therefore there is no established method of monitoring fatigue.

Group (2) includes stress markers [14-17] for acute stress values. However, the issues of heterogeneous concentration of salivation and the pain of taking blood samples remain unsolved. Group (3) includes a subjective symptom examination [18-20]. It is useful for feelings of fatigue, and is widely used.

We need a method for measuring mental fatigue, but the current methods depend on the individual’s personal judgment based on medical examinations with an interview by a doctor. For that reason, degree of fatigue is currently measured by subjective self-reported symptoms of fatigue. A quantitative method of measuring mental fatigue is needed, together with a questionnaire for general assessment.

In this study, in order to construct a quantifiable method of estimating mental fatigue, we propose a method of measuring degree of fatigue by LOM. Because the mechanism of mental fatigue has not been clearly established, the complicated phenomenon of fatigue was evaluated by biomedical signs. Because mental fatigue is related to the immune system, the autonomic system and the circulatory system, the data is in constant change, and it is difficult to build a mathematical model of the phenomenon of fatigue. We cannot convert fatigue into numbers.

Using several sensors would be a strain for subjects in measuring biomedical signs, so we should select a limited number of sensors and estimate fatigue from limited information. We made a database from many variables of our past data, in which the sympathetic nerves and parasympathetic nerves influenced fatigue-related biomedical signs, and those biomedical signs could be converted to nonlinear and short-time.

JIT modeling (Just-In-Time modeling) [21-23] as local modeling is different from usual model building methods. It selects a sample query neighborhood from a database at only the query time. A local model is built by using the sample at that time, and it outputs the estimate by using the local model each time. For this reason, the method of JIT modeling can catch the phenomenon at it changes over time. Therefore we decided it would be effective to use JIT modeling. We used LOM [1, 2], one of the JIT modeling.

3. Subjects and Methods

3.1 Subjects

The subjects in our study were 10 male medical university students, average age 21.8 ± 2.2 (mean± SD, 18 to 26 years old). The average Visual Display Terminals (VDT) experience was 4.2 ± 2.5 years (mean± SD, 0 to 9 years). Preliminary survey sheets were provided to the subjects the day before the experiment, and appropriate instructions (abstaining from alcohol and coffee, sufficient sleep, etc.) were given. All the subjects were nonsmokers. The subjects had no training in VDT Operation for this experiment.

3.2 VDT operation

To make new mental fatigue values by biomedical signs, we devised a work task based on the stress-strain-effects model of ISO 10075 [24, 25]. The stress-strain-effects model of ISO 10075 is presented in Fig. 1. We made a selection “TASK” for the induction problem in fatigue [26]. The Ministry of Health, Labour and Welfare published the guideline of Health and Safety in operation of VDT, recommending the prevention of mental and physical fatigue during operation of VDT [27]. It is the input of data, drawing pictures, and programming with keyboards and a mouse. Mental arithmetic operation induces mental fatigue. Then we selected VDT Operation of mental arithmetic tasks. The VDT Operation included VDT.

| Group | Item |
|-------|------|
| Speech Sound |
| Fluctuation of Blood Flow Pulse Wave |
| Diagnostic Audiometry |
| Heart Rate Variability (HRV) |
| Critical Fusion Frequency of Flicker |
| Alpha Wave of Electroencephalogram |
| Optical Topography |
| Advanced Trail Making Test (ATMT) |
| Catecholamine |
| Cortisol |
| Blood DHEA-S |
| Natural Killer Cells Activity |
| Cytokine |
| Urine 17-KS-S/17-OHCS |
| Catecholamine |
| Cortisol |
| Saliva Human Herpes Virus 6 (HHV-6) |
| Questions about subjective feelings of fatigue |
| NASA-Task Load Index (NASA-TLX) |
| Cumulative Fatigue Symptoms Index (CFSI) |
| The General Health Questionnaire (GHQ) |
| Profile of Mood States (POMS) |
| Psychological Test Self-Rating Depression Scale (SDS) |

Table 1 Method of estimating stress and fatigue [8] (Courtesy of Yuriko Hachiya, Waseda’s doctoral thesis, p.14, 2012, Table 2-1)
3.3 Outline of experiments

The experimental schedule is presented in Fig. 2. After assuming a relaxed seated position for 10 minutes, the subjects performed two repeated sessions of a mental arithmetic task for 30 minutes each session with a 30-minute break. Subjective symptoms of feelings of fatigue score were evaluated on a 10-point scale.

3.4 Biomedical signs [6]

The alteration of the R-R interval of electrocardiography, the increase in subsonic frequencies in the electromyogram, and certain other parameters are biological data related to fatigue; however, there is no consensus on their interpretation [28]. In addition, there are no established methods of direct measurement. Thus, we first examined the selection of biological parameters to be measured.

We considered physiological values, including respiratory functions (respiratory rate), nerve functions (brain-waves, electromyogram), circulatory functions (blood pressure, electrocardiogram, heart rate, skin blood flow), visual functions (blinking), thermoregulation functions (surface skin temperature measured by thermocouple sensors and a Thermotracer infrared imaging camera), and metabolic and secretory functions (perspiration, salivation). In addition, we controlled for the time of day of the experiment, the measurement time, the measurement equipment, the measurement methods, sensor placement, the operation of the text input management software, and the physical condition of the test subjects. We also conducted preparatory experiments to verify the validity of the measurement items. The preparatory experiments were performed six times on six subjects; we checked whether the subject felt pain or discomfort, whether the tests were tiresome because of too many measurement items, whether the tests might be potentially harmful to the subjects’ health, and so on. Using the results, we refined the measurement items. Eventually, the measurements were restricted to the following parameters: the surface skin temperature of the forehead and the tip of nose, the pulse rate, the palm skin blood flow, and the respiratory rate. The tip of the nose surface skin temperature is believed to be affected by neurogenic stress caused by emotional response and tension [29]. When one feels discomfort, the blood flow decreases due to sympathetic nerve activity, and the temperature drops [30]. The forehead surface skin temperature is related to the central nervous system, and usually does not change much [31]. The skin blood flow was obtained as the product of the speed and erythrocyte volume measured in the palm using a laser-Doppler blood flow meter. This study was approved by the Ethics Committee of the University of Occupational and Environmental Health, Japan.

3.5 Mental arithmetic task software

Mental arithmetic task software is given in Fig. 3, which shows the input screen. It was developed in order to measure the subjects’ work in the experiments. The subjects were asked to add 3 numbers, and enter the last digit. The process continued for 30 minutes. The subjects were asked to enter their fatigue rating at intervals of 10 minutes.

3.6 Experimental environment

The experiments were performed at a room temperature of 25 °C, with humidity of 60%, and the subjects’ clothing weight of 140g [32].
4. JIT Modeling and LOM

With the development of the computing machine and the database system, accumulating and retrieving a large amount of data at a high speed have become possible. Models such as locally weighted JIT modeling have attracted much attention because they can cope with changes in process characteristics as well as nonlinearity. To apply JIT modeling [21-23], LOM can be used. LOM is one of the computational methods in JIT modeling. We used a modified form of LOM.

An object’s process is a nonlinear dynamic system. The practical method based on JIT modeling calls up past, similar operations of data that have been searched, and the prospective operation data is estimated.

A schematic diagram of LOM [1-5] is presented in Fig. 4. The LOM is one of the JIT modeling methods. It is a technique that makes retrieval of “neighbor” data more efficient by using a “stepwise method” and quantization. The stepwise method decreases the dimensions of multidimensional space of the actual process. In addition, the multidimensional space is quantized.

An object’s process is a nonlinear dynamic system, and characteristics of the system are given by a regression model expressed in the following equation (1).

\[
y(t+p) = f(y(t), y(t-1), \ldots, y(t-n_y), \quad u(t-d), u(t-d-1), \ldots, u(t-d-n_u)) \ldots (1)
\]

where

- \( u(t) \): the control input vector of system at time \( t \)
- \( y(t) \): the observational output of system at time \( t \)
- \( n_y \): the order of control input vector
- \( n_y \): the order of observational output vector
- \( p \): the estimated time (or the predicted time)
- \( d \): the time delay
- \( f \): an unknown nonlinear function
- \( t \): the time

The system input vector \( x^i \) and the system output \( y^i \) are further redefined in the following (2) and (3).

\[
y^k \equiv \{y(k), y(k-1), \ldots, y(k-n_y), \quad u(k-d), u(k-d-1), \ldots, u(k-d-n_u)\} \ldots (2)
\]

\[
x^k \equiv \{y(k), y(k-1), \ldots, y(k-n_y), \quad u(k-d), u(k-d-1), \ldots, u(k-d-n_u)\} \ldots (3)
\]

As time passes, a large amount of data, composed of the system input vector \( x^i \), the system output \( y^i \), for example \( (x^i, y^i), (x^2, y^2), \ldots \), is stored in the system as data sets \( \{x^k, y^k\}, (k = 1, 2, \ldots) \), where \( k \) is the discrete time. Then, JIT modeling finds out the output of the nonlinear function \( f \) from the stored data sets \( \{x^k, y^k\} \) whenever they are required to be estimated (or predicted, controlled).

For example, when it becomes necessary to estimate a system state at time \( t \), the present system state \( x^k \) is defined as the demand point. Neighboring data \( \{x^k, y^k\} \) \((k < k)\) similar to the demand point as past observed process data in the database are selected. When a number of data sets are obtained, a local model to interpolate output of the dataset will be constructed. By using the local model, the system output \( y^k \) is estimated. Then, the local model is discarded and neighboring data sets in measured data sets in an updated database are selected for the next estimation. The LOM [1-5] makes the retrieval of neighboring data more efficient by using the stepwise method and quantization. The stepwise method decreases the dimension of multidimensional space of the actual process. In addition, the multidimensional space is quantized. The stepwise method is a technique that adds and deletes input variables by statistical testing to decrease input variables within the bound enough for practical use in the regression model. In this study, the \( y \) is mental fatigue. Mental fatigue is related to the immune system, the autonomic system and the circulatory system; it is nonlinear, and it changes over time. It is difficult to build a mathematical model of the phenomenon of fatigue.
In this paper, the degree of similarity \( S(k_i,k_j) \) between demand data past data is defined as the Euclidean distance, as follows.

\[
S(k_i,k_j) = \sqrt{\sum (x^i - x^j)^2}
\]

Datasets of setting number that have small \( S(k_i,k_j) \) are adopted as the neighboring datasets.

LOM is one of the local modeling methods used to identify the characteristics of fatigue based on information derived from observation of biomedical signs. The process flow of the LOM system for human fatigue is presented in Fig. 5. The processing flow consists of a process for updating measured data.

The processing in each time of obtaining data updating is presented in (a) to (c), and the processing in each time of feelings of fatigue demanding is presented in (1) to (7).

(a) The obtained data (feelings of fatigue and biomedical signals) for each subject is accumulated for Large-scale Data-based.

(b) The variable is generated by delayed time for each variable, and the variable is narrowed down to a high contribution variable concerning the estimated target by the Stepwise method.

(c) The concentrated variables are put into the database.

(1) The Query data and setting information are taken out.

(2) The obtained data is taken out from the database.

(3) The obtained data are normalized and quantized.

(4) The neighboring data are normalized and quantized.

(5) The neighboring quantum data of the Query point are retrieved on setting numbers.

(6) Local Model is constructed from retrieved neighboring data, and feelings of fatigue score is estimated.

(7) Local Model is discarded after every estimation.

5. Results and Discussions

For the purpose of using LOM, we considered setting the number of moving-average points so as to streamline the waveforms. Following is the result of our experiment.

First, we set the number of moving-average points for every biological parameter. A typical case is shown in Fig. 6 (pulse rate for first experiment in case of subject A). Here we compared the raw waveform to the moving averaged results, and selected the number of moving-average points to obtain a smooth noise-free waveform, while preserving the general pattern of the original waveform. The other biological parameters were examined in the same way to select the number of moving-average points; namely, 8 for the surface skin temperature at the forehead and tip of nose, 20 for the pulse rate and respiratory rate, and 30 for the skin blood flow.

The result of the fatigue score predicted by LOM system is described. The input variable was 306 items by making delay 600 seconds. There are 16 data items of a high contribution ratio of F-test value higher than 10 for the feelings of
fatigue score selected by the stepwise method from 306 data items on past data variables after smoothing. F value is the contribution ratio for the feelings of fatigue score.

The selected variables by the stepwise method are presented in Table 2. The 16 data items were respiratory rate at 10, 250, 460, 600 seconds before and present, skin blood flow at 40 and 360 seconds before, pulse rate at 10, 270 and 510 seconds before, temperature (forehead) at 10, 600 seconds before and present, temperature (tip of nose) at 10, 250 seconds before and present. The F value of respiratory rate at 600 seconds before was the highest. The respiratory rate is assumed to reflect mental activity.

Second, the estimated feelings of fatigue were reproduced by LOM using 16 data items. The sampling time was 10 seconds. The number of data sets was 9,853. The quantized number for the retrieved space of database was 100. We could confirm that the estimated fatigue score is similar to the actual fatigue score. For example, the actual and estimated fatigue score by LOM every 10 seconds (C: third experiment in the case of subject C; D: second experiment in the case of subject D; J: second experiment in the case of subject J.) is presented in Fig. 7. The correlation coefficients between actual and estimated feelings of fatigue were 0.8285, 0.7002, and 0.8123 in C, D and J, respectively. The estimated value is very similar to the actual fatigue score, as predicted by the equation. The correlation coefficient between the actual and estimated feelings of fatigue by LOM and Multiple Regression Analysis in 40 experiments is presented in Table 3. The correlation coefficient between the actual and estimated feelings of fatigue by LOM was 0.70 to 0.99 in 14 experiments out of 40.

The result of fatigue score predicted by Multiple Regression Analysis is described for comparison with the LOM system. For Multiple Regression Analysis, the database is built on only 5 data items, and feelings of fatigue score by linear interpolation is measured. The sampling was done every 10 seconds. The number of data sets was 9,853. The correlation coefficient between actual and estimated feelings of fatigue was 0.70 to 0.99 in 3 experiments out of 40 by Multiple Regression Analysis. It was difficult to get an estimated fatigue score simulating actual fatigue by the Multiple Regression Analysis method. Therefore the LOM system was comparatively higher than the correlation coefficient result of Multiple Regression Analysis method, because the feelings of fatigue was estimated by composing the local model with changing time.

The score of actual and estimated feelings of fatigue for the second experiment in the case of subject H by LOM every 10 seconds is presented in Fig. 8. In addition, differences between the actual and estimated fatigue scores and Similarity (Data of distance) in the second experiment in the case of subject H by LOM every 10 seconds is presented in Fig. 9. Similarity was defined as the Euclidean distance between the query data and past neighbor data.

In Fig 8, when time was 300 seconds (point “a”), the estimated feelings of fatigue was not similar to the actual feelings. But when the time was 500 seconds (point “b”), the estimated feelings of fatigue was similar to the actual feelings. In Fig 9, when the time was 300 seconds, the simi-
Table 3  Correlation coefficient of actual and estimated feeling of fatigue by Multiple Regression Analysis and LOM for each subject

| Subject (year) | Age | Sex | *VDT experience (year) | **LOM | Multiple Regression Analysis |
|---------------|-----|-----|------------------------|-------|-----------------------------|
|               |     |     | correlation coefficient | p-value | correlation coefficient | p-value |
| A 26 M 4      |     |     | 0.8262 1.35E-28        | -0.3630 0.272748 |
|               |     |     | 0.4279 1.87E-21        | -0.0444 0.81E-11  |
|               |     |     | 0.4598 1.83E-17        | -0.2229 1.48E-08  |
|               |     |     | 0.3523 5.03E-06        | 0.1222 0.001618  |
| B 21 M 0      |     |     | 0.7802 1.25E-06        | 0.4736 0.000199  |
|               |     |     | 0.6918 1.98E-20        | 0.4007 1.93E-09  |
|               |     |     | 0.5332 7.78E-22        | 0.5708 7.39E-47  |
|               |     |     | 0.5845 5.84E-09        | 0.3128 1.12E-71  |
| C 19 M 6      | 4   |     | 0.6654 0.002224        | 0.7749 0.263086  |
|               |     |     | 0.1692 3.36E-51        | 0.3780 0.836834  |
|               |     |     | 0.8251 1.39E-05        | 0.5069 0.034759  |
|               |     |     | 0.4049 8.56E-20        | 0.3999 0.014617  |
| D 18 M 3      | 3   |     | 0.8848 2.89E-06        | 0.2912 0.579121  |
|               |     |     | 0.7002 1.1E-07         | 0.1719 3.74E-05  |
|               |     |     | 0.8235 2.2E-17         | -0.0447 4.02E-06 |
|               |     |     | 0.4242 2.43E-31        | 0.2855 8.89E-06  |
| E 21 M 9      | 4   |     | 0.2611 5.99E-37        | 0.6128 4.22E-29  |
|               |     |     | 0.4653 1.59E-29        | 0.1129 4.48E-06  |
|               |     |     | 0.3950 3.79E-07        | 0.2802 1.51E-14  |
|               |     |     | 0.3011 0.001741        | 0.3207 0.317261  |
| F 23 M 6      | 6   |     | 0.2093 0.105334        | 0.5892 0.001158  |
|               |     |     | 0.2125 3.2E-16         | 0.0075 4.59E-12  |
|               |     |     | 0.7791 0.327988        | 0.2632 0.11776  |
|               |     |     | 0.0418 1.47E-08        | -0.1171 9.07E-12 |
| G 23 M 6      | 6   |     | 0.2926 1.37E-11        | 0.2930 1.64E-31  |
|               |     |     | 0.8268 5.09E-33        | 0.6497 0.013022  |
|               |     |     | 0.8301 0.019764        | 0.0838 8.4E-31   |
|               |     |     | 0.9183 8.86E-10        | 0.1293 0.790512  |
| H 21 M 3      | 3   |     | 0.5469 3.32E-13        | 0.0536 2.58E-07  |
|               |     |     | 0.5022 0.003687        | 0.5847 0.000162  |
|               |     |     | 0.4084 7.38E-12        | 0.5184 9.698E18  |
|               |     |     | 0.4545 1.98E-10        | 0.5124 0.819139  |
| I 23 M 2      | 2   |     | 0.2615 9.01E-05        | 0.1528 0.237741  |
|               |     |     | -0.0651 3.52E-12       | -0.2597 0.18321  |
|               |     |     | 0.4142 3.99E-12        | 0.7188 0.001296  |
|               |     |     | 0.1155 3.36E-11        | 0.3769 0.005082  |
| J 23 M 4      | 4   |     | 0.9132 4.32E-23        | 0.2480 3.03E-07  |
|               |     |     | 0.8123 0.291322        | 0.2164 9.33E-06  |
|               |     |     | -0.2783 5.41E-22       | -0.3755 5.77E-14 |
|               |     |     | 0.6474 0.007069        | 0.3129 3.58E-10  |

*VDT: Visual Display Terminal; **LOM: Large-scale Data-based Online Modeling

Table 3. Correlation coefficient of actual and estimated feeling of fatigue by Multiple Regression Analysis and LOM for each subject.

Table 3 illustrates the correlation coefficient of actual and estimated feeling of fatigue for each subject using Multiple Regression Analysis and LOM. The table shows the correlation coefficient and p-value for the actual and estimated fatigue scores, as well as the correlation coefficient and p-value for the Multiple Regression Analysis.

The focal point of this study is the estimation of acute mental fatigue from biomedical signs using the LOM method. We proposed that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method. We chose the LOM method because it can cope with changes in process characteristics as well as nonlinearity. We selected VDT Operation of a mental arithmetic task and devised a work task based on the stress-strain effects model of ISO 10075 and the guideline of Health and Safety administration on VDT. After preparatory experiments to verify the validity of the measurement items, the measurements were restricted to the surface skin temperature of the forehead and the tip of nose, the pulse rate, the palm skin blood flow and the respiratory rate data, making it possible to estimate the feelings of fatigue more exactly. We suggest that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method.

To exclude individual differences and daily condition differences, the conditions were controlled for age, VDT experience, nonsmoker, room temperature, humidity and the subjective factors. Individual differences and daily condition differences are large, not only in objective valuation but also in estimation. Therefore we suggest that the method of estimating fatigue score by correlation actual survey should use a fatigue study.

6. Conclusions

We proposed that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method. We chose the LOM method because it can cope with changes in process characteristics as well as nonlinearity.

Accordingly, if a local model with changing time is constructed using neighboring data of small similarity, the estimated feelings of fatigue is able to be more similar to actual feelings of fatigue, and similarity can be used as an indicator of degree of estimation. Moreover the advancement of prediction accuracy is expected by storing the surface skin temperature of the forehead and the tip of nose, the pulse rate, the palm skin blood flow and the respiratory rate data, making it possible to estimate the feelings of fatigue more exactly. We suggest that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method.

Table 3 illustrates the correlation coefficient of actual and estimated feeling of fatigue for each subject using Multiple Regression Analysis and LOM. The table shows the correlation coefficient and p-value for the actual and estimated fatigue scores, as well as the correlation coefficient and p-value for the Multiple Regression Analysis. We proposed that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method. We chose the LOM method because it can cope with changes in process characteristics as well as nonlinearity. We selected VDT Operation of a mental arithmetic task and devised a work task based on the stress-strain effects model of ISO 10075 and the guideline of Health and Safety administration on VDT. After preparatory experiments to verify the validity of the measurement items, the measurements were restricted to the surface skin temperature of the forehead and the tip of nose, the pulse rate, the palm skin blood flow and the respiratory rate data, making it possible to estimate the feelings of fatigue more exactly. We suggest that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method.

Table 3 illustrates the correlation coefficient of actual and estimated feeling of fatigue for each subject using Multiple Regression Analysis and LOM. The table shows the correlation coefficient and p-value for the actual and estimated fatigue scores, as well as the correlation coefficient and p-value for the Multiple Regression Analysis. We proposed that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method. We chose the LOM method because it can cope with changes in process characteristics as well as nonlinearity. We selected VDT Operation of a mental arithmetic task and devised a work task based on the stress-strain effects model of ISO 10075 and the guideline of Health and Safety administration on VDT. After preparatory experiments to verify the validity of the measurement items, the measurements were restricted to the surface skin temperature of the forehead and the tip of nose, the pulse rate, the palm skin blood flow and the respiratory rate data, making it possible to estimate the feelings of fatigue more exactly. We suggest that it is possible to estimate the degree of acute mental fatigue from biomedical signs using the LOM method.
of data sets was 9,853. The quantized number for the retrieved space of database was 100.

The correlation coefficient between the actual and estimated feelings of fatigue by LOM was 0.70 to 0.99 in 14 experiments out of 40, and by Multiple Regression Analysis it was 0.70 to 0.99 in 3 experiments out of 40. The experiment number of 0.70 to 0.99 of a correlation coefficient by the LOM system was comparatively higher than the Multiple Regression Analysis method. In addition, if Similarity was small, the difference between the actual and estimated fatigue score was small. We could estimate the feelings of fatigue.

We propose this method for determining the reliability of estimating “degree of fatigue” by distance of neighboring data.

Acknowledgments

We express our gratitude to Mr. Hiroyuki Izumi of the Department of Ergonomics, University of Occupational and Environmental Health, for his cooperation in the experiments.

References

[1] M.Ito, S.Matsuzaki, N.Odate, K.Uchida, H.Ogai and K.Akizuki: Large scale database online modeling for blast furnace, Proc. 2004 IEEE CCA, pp. 906-911, 2004.
[2] M.Ito, S.Matsuzaki, K.Ogai, N.Odate, K.Uchida, S.Saito and N.Sasaki: Large scale database-based online modeling blast furnace operation, Tetsu-to-Hagane, ISJJ, Vol. 90, No. 11, pp. 59-66, 2004.
[3] M.Ito, S.Matsuzaki, H.Ogai, K.Mori, K.Uchida, S.Saito and N.Sasaki: Application of large scale database-based online
modeling of blast furnace operation, Proc.16th IFAC World Congress, Prague CD-ROM, 2005.

[4] H.Ogai, M.Ogawa, K.Uchida, S.Matsuzaki and M.Ito: Development of an operation support system for the blast furnace in the ironmaking process: Large-scale database-based online modeling and integrated simulators, SICE Journal of Control, Measurement, and System Integration, Vol. 1, No. 3, pp. 199-206, 2008.

[5] Y.Akaike, K.Higashi, N.Tanaka, H.Furuya, M.Ogawa, Y.Yeh, T.Tokunaga and H.Ogai: Application for large scale database-based online modeling of melting furnace, Preprints of the IFAC Workshop on Automation in the Mining, Mineral and Metal Industries, pp. 120-125, Gifu, Japan, September 10-12, 2012.

[6] Y.Hachiya, H.Izumi, M.Ogawa, S.Kawanari, K.Mori and H.Ogai: Measurement of degree of fatigue by large-scale database-based online modeling, SICE Trans. on Industrial Application, Vol. 10, No.10, pp. 81-90, 2011. (in Japanese)

[7] Y.Tanaka and S.Wakida: Biomarkers of stress and fatigue, Folia Pharmacol. Jpn., Vol. 137, p. 186, 2011. (in Japanese)

[8] Y.Hachiya: Analysis of biological information of fatigue and method for estimating degree of fatigue, Waseda’s doctoral thesis, p. 14, 2012. (in Japanese)

[9] B.Mulder, H.Veldma, F.van der Veen et al.: On the effects of mental task performance on heart rate, blood pressure and its variability measures, M. D. I Rienzo et al. (ed.), Blood Pressure and Heart Rate Variability, Amsterdam, IOS Press, pp.153-166, 1992.

[10] M.Pagani, R.Furlan, P.Pizzinelli et al.: Spectral analysis of r-r variability measures, M. D. I Rienzo et al. (ed.), Blood Pressure and Heart Rate Variability, Amsterdam, IOS Press, pp.153-166, 1992.

[11] E.Simonson, N.Enzer, and S.S.Blankstein: Influence of flicker, during mental stress in humans, J Hypertens, Vol. 7 (Supple 6), and arterial variabilities to assess symatho-vagal interaction

M.Pagani, R.Furlan, P.Pizzinelli et al.: Spectral analysis of r-r variability measures, M. D. I Rienzo et al. (ed.), Blood Pressure and Heart Rate Variability, Amsterdam, IOS Press, pp.153-166, 1992.

[12] T.Ikeguchi and K.Aihara: Lyapunov spectral analysis on J. Expr. Psychol., Vol. 29, pp. 252-255, 1941.

[13] E.Simonson, N.Enzer, and S.S.Blankstein: Influence of flicker, during mental stress in humans, J Hypertens, Vol. 7 (Supple 6), and arterial variabilities to assess symatho-vagal interaction

[14] S.G.Hart and L.E.Staveland: Development of NASA-TLX (task load index) results of empirical and theoretical research, P. A. Hancock and N. Meshikati (eds.), Human Mental Workload, pp.139-193, 2000.

[15] S.Ushida and H.Kimura: Just-in-time approach to nonlinear identification and control, Journal of the Society of Instrument and Control Engineers, Vol.44, No. 2, pp. 102-106, 2005.

[16] F. Nachreiner: Review article international standards on mental work-load -The ISO 10075 Series-, Industrial Health, Vol. 37, p. 129, 1999.

[17] Secretariat of ISO/TC159/SC1/WG1: Revision of ISO6385 working document, Result of the meeting on the 29th of September 2000, ISO/TC159/SC1/WG1 N017-00, 2000.

[18] S.G.Hart and L.E.Staveland: Development of NASA-TLX (task load index) results of empirical and theoretical research, P. A. Hancock and N. Meshikati (eds.), Human Mental Workload, pp.139-193, 2000.

[19] Ministry of Health, Labour and Welfare: Annual report on health, labour and welfare 2003-2004 -attaining safety and peace of mind with information and collaboration-, Ministry of Health, Labour and Welfare Press, 2003.

[20] A.Seo et al.: Application of Surface Electromyography to Ergonomics, ISL Publ., 2004.

[21] K.Ohara: Skin temperature, H.Yoshimura, K.Ogata and S.Itoh (eds.), Essential Problems in Climatic Physiology, Nankodo, pp.109-143, Tokyo, 1960.

[22] J.J.van Lieshout, W.Wieling, J.M.karemaker and D.L. Eckberg: The vasovagal response, Clin Sci (Lond), Vol.81, No. 5, pp. 575-586, 1991.

[23] J.Werner and T.Reents: A contribution to the topography of temperature regulation in man, Eur. J. Appl. Physiol, Vol. 45, pp. 87-94, 1980.

[24] Guidelines for occupational health management of VDT operations with comments, JISHA, 2002.

[25] D.G.Altman: Relation between two continuous variables, Practical Statistics for Medical Research, pp. 277-283, 1991.

[26] M.Feinleib, MS.Garrison, N.Bornhant et al.: Studies of hypertension in twins, O Paul (ed), Epidemiology and Control of Hypertension, New York, Grune & Stratton, pp. 3-20, 1975.

Yuriko Hachiya received her Associate degree from the University of Occupational and Environmental Health, Japan, in 1983, and her M.E. and Ph.D. degrees in information, production and systems engineering from Waseda University in 2005 and 2012, respectively. Since 1983, she has been with the Department of Health Center, the University of Occupational and Environmental Health, Japan. Her research interest is visualization of human fatigue. She is a member of SICE, IEEJ and JSOH.
Masatoshi Ogawa received his M.E. and Ph.D. degrees in information, production and systems engineering from Waseda University in 2005 and 2008, respectively. He worked at the Information, Production, and Systems Research Center of Waseda University from 2007 to 2011. Since 2011, he has been a researcher at FUJITSU LABORATORIES LTD. He received the outstanding paper award by General Chair of ICCAS-2013 from ICROS and the Best Paper Award from SICE in 2013. His current research interests are modeling, simulation and control application for industrial processes. He is a member of SICE and IEEJ.

Sho Kawanari graduated from the Kure National College of Technology in 2008. He received his M.E. degree in information, production and systems engineering from Waseda University in 2010.

Hideaki Suzuki received his M.D. and Ph.D. degrees from Tohoku University School of Medicine in 1983 and 1993, respectively. In 1983, he joined the Department of Otolaryngology of Tohoku University School of Medicine. He studied at Washington University and Johns Hopkins University from 1989 to 1991, and was promoted to Assistant Professor of the Tohoku University School of Medicine in 1996. He was appointed to Professor and Chairman of the Department of Otorhinolaryngology of the University of Occupational and Environmental Health in 2003. His main research interest is the pathogenesis of inflammatory upper air-way diseases.

Harutoshi Ogai received his B.E. degree from Waseda University in electrical engineering in 1974, and his M.E. and Ph.D. degrees from Tokyo Institute of Technology in control engineering in 1976 and 1997, respectively. In 1976, he joined Nippon Steel Corp. He was engaged in the development of steel production control. Since 2003, he has been a Professor at Waseda University. His research interests are process control, process monitoring, simulation techniques, autonomous driving control, and engine control, etc. He is a member of SICE, ISIJ, and other societies.

(Received June 6, 2014; revised May 3, 2015)