Proposal and Evaluation of An Adaptive Agent for Stress Control Training using Multimodal Biological Signals

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ABSTRACT
In this research, we aim to develop a training system that allows individuals to control their own stresses autonomously. For this, we propose a sound presentation agent that provides adaptive training according to the user's stress state with observations of probabilistic environment states using reinforcement learning and multimodal biological signals. In addition, we verify the superiority of using multimodal biological signals through a simulation experiment and evaluate the system. From the results, it is seen that the agent presents more appropriate sounds using biological signals having different features extracted from the same source signal. In future, we will conduct subject experiments based on the results of this research and compare those results with the simulation results in order to confirm the validity of the simulation.

ACM Classification Keywords
H.5 Information Interfaces and Presentation (e.g. HCI)

Author Keywords
Multimodal Biological Signals, Adaptive Agent System, Simulation

INTRODUCTION
The excessive stress in social life causes decrease in productivity and the onset of disease. In order to reduce such negative influences, it is necessary for each individual to acquire ways to control their own stresses autonomously. Mindfulness meditation is one way to realize this, and there are many support systems for performing mindfulness meditation [9][10]. Such systems are mainly divided into two types: one that teaches users how to perform mindfulness meditation and the other that estimates the proficiency or state of mindfulness meditation from the user's biological signals. Following these previous studies, we focus on developing a stress control training system based on mindfulness meditation. Although many researchers have tried to construct a support system for mindfulness meditation, a system that adaptively changes the training policy based on the states of stress estimated from a user's reaction has not yet been realized. To overcome this problem, we have developed a system to support the acquisition of stress control.

This training system employs a sound presentation agent, which uses a stimulus sound assumed to bring the user to a high or low stress state, and makes the user try and maintain that stress state at a constant level. In addition, it changes the stimulus sound load according to the estimated stress state of the user in order to make the training more efficient. We assume that users' stress state can be estimated from the noise and delay of biological signals. Thus, the estimation involves both fluctuations caused by training effects and probabilistic factors.

In this research, we aim to construct a training system that adapts to the user's stress state through observations of probabilistic environment states, and to study the framework of reinforcement learning using multimodal biological signals. In addition, we perform simulation experiments with the generated biological signals using a probabilistic model, which utilizes the stress values of the user model as the parameters, in order to evaluate the framework of reinforcement learning.

OBSERVATIONS OF BIOLOGICAL SIGNALS
The partially observable Markov decision process (POMDP) is an extension of the Markov decision process (MDP), and consists of tuples of <S, A, T, R, Ω, O>. The first four elements express the Markov decision process (S: State, A: Action, T: Transition, and R: Reward), and the later two are finite observations and probability distributions of results based on each state and action. In POMDP, the agents cannot observe

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the state of the environment directly. Instead, the agents observe the probabilistic state of the environment based on their actions and their results.

Our sound presentation agent estimates the stress state of the user based on two different types of biological signals: Electroencephalogram (EEG) and Electrocardiogram (ECG).Among the several indices calculated from EEG, we select the occipital alpha activity as the stress index, because this signal indicates a global neural activity related to the subjective arousal level [2]. Though the signals from EEG contain a large amount of noise, which are caused by sources other than neural activity such as movements of the eyes and the body [6], it has an advantage in terms of reactivity; EEG signals are generated rapidly after the occurrence of neural events [1].

With regard to ECG, we assume that LF/HF (Low Frequency/High Frequency) partially reflects the stress state of the user. LF/HF is regarded as an index of the sympathetic nervous system activity, and it incorporates a relatively small amount of noise as compared to EEG. However, since the calculation of this index needs longer sampling time, this index is necessarily a mixture of the stress that has occurred during several time points.

Therefore, in our sound presentation agent, two different POMDPs are involved: one for the influence of large noise in the alpha activity and the other for the mixture of past stress states in LF/HF. Considering these characteristics of each biological signal, we hypothesized that combining these two signals improves the accuracy of stress estimation.

STRESS CONTROL TRAINING SYSTEM

In our training system, the users are required to control their stress to bring the alpha activity and the LF/HF closer to a certain baseline while they are exposed to one of the two sound stimuli (low/high stress sounds). In this study, the baseline is set to the average value of each biological signal for a fixed time in the natural state. To guide the user's stress state to the baseline, the sound presentation agent presents high stress sounds when the agent estimates the user's stress state as low, and low stress sounds when the agent estimates it as high.

In order to change the training policy of the agent adaptively according to the user's stress state, we use reinforcement learning. The value function of the user's stress state and the sounds presented by the agent are updated by Q learning, which is a basic framework of the reinforcement learning used in POMDP:

$$Q(s,a) = Q(s,a) + \alpha(r + \gamma Q(s',a') - Q(s,a)). \qquad (1)$$

In the framework of the proposed reinforcement learning, the state s takes one of the four states, combining the higher of the states lower than the baseline of alpha activity with LF/HF. Action a is selected from the high stress or low stress sound presentation. s' and a' are the states and actions after the sound presentation, respectively. The reward r is positive when the observed alpha activity and LF/HF values are close

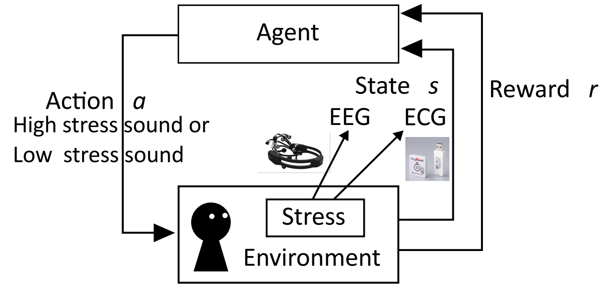

Figure 1. Relationship between the sound presentation agent and the user. The agent estimates the user's stress state through EEG and ECG with probabilistic fluctuation.

to the baseline, and is negative when the observed alpha activity and LF/HF values are far from the baseline. α is the learning rate, and γ is the discount factor.

SYSTEM ARCHITECTURE

The sound presentation agent is incorporated into the system, which is created based on an existing research [7]. As shown in Fig. 1, Emotiv EPOC^{+}, which is an electroencephalograph manufactured by EMOTIV, records the EEG, and myBeat, manufactured by UNION TOOL, records the ECG. In this system, during training, the users close their eyes and attempt to control their own stress while being exposed to the high/low stress sounds. The users engaged in this training, at least for a 10 min session at a time. In one session, there are 100 trials in which the same sound lasts for 6 s. For each trial, the agent updates the sound presentation policy with reinforcement learning based on the observed biological signals and determines the next presentation sound.

SIMULATION EXPERIMENT

We evaluate the above sound presentation agent through simulations, although an experiment with human participants is needed to evaluate the agent, because a large number of participants are required to eliminate the influence of individual differences, which are assumed to be especially large in the case of biological signals. Before conducting human experiments, it is reasonable to conduct a simulation experiment to examine the experimental settings, such as the required performance of the measuring device for biological signals, or the trials needed for the training of stress control.

In this simulation, the user model is used as a substitute for human participants. We set the baseline of the stress value for the user model to 50, and use it as the initial value. This stress value shifts in the range 0-100. It increases by 10 when a high stress sound is presented, and decreases by 10 when a low stress sound is presented. The alpha activity and LF/HF used in the simulation are probabilistically generated from the normal distribution [3][4]. The parameter μ of the normal distribution expresses the stress value of the user model, and σ expresses the noise (σ is 30 for alpha activity and 10 for LF/HF). The μ of LF/HF is taken as the average of the stress values for 5 trials, in order to simulate the mixture of past stress states.

For the above user model, the sound presentation agent performs "estimate of stress state," "selection of presentation sound," and "sound presentation." Considering this as one trial, one simulation run repeats 500 trials equivalent to 5 sessions. We conducted 50 simulation runs for each of the following five simulation conditions: using both alpha activity and LF/HF, using alpha activity or LF/HF only, and using alpha activity or LF/HF twice, both of which are generated from the same probability model.

Moreover, in order to verify the extent to which the framework of reinforcement learning using alpha activity and LF/HF allows the noise of alpha activity, the same simulation is conducted with five kinds of normal distribution of alpha activity: σ =10, 20, 30, 40, and 50.

RESULTS

Fig. 2 shows how the stress state of the user model is changed through the training guided by the sound presentation agent. In order to show how much the agent is able to influence the stress value of the user model so that it approaches the baseline, the vertical axis of the figure indicates the moving average of the distance between the stress value in the user model and the baseline defined as follows:

$$d_t = \frac{1}{W}\sum_{i=1}^{W} |s_i - B| \tag{2}$$

$$d_{mean} = \frac{1}{N}\sum_{i=1}^{N} d_i \tag{3}$$

where W is the window size for calculating the average, N is the number of runs used for the average, and B is the baseline of the stress value for the user model. In this study, we set $W = 100$, $N = 50$, $B = 50$, and employed three conditions, varying the type of biological signals used by the agent: "alpha + LF/HF" where the agent uses both the signals to estimate the stress (the red line), "alpha" where the agent uses only alpha (the green line), and "LF/HF" where the agent uses only LF/HF (the blue line). From the figure, we can observe that the smallest distance is obtained for "alpha + LF/HF" throughout the training sessions, which indicates the advantage of using multimodal biological signals to stabilize the stress value.

Although Fig. 2 successfully illustrates the advantage of the proposed framework, we need to note that the frequencies of observation were different for different conditions. To ensure uniformity in an effect of the frequency of observations, we added two more conditions, where the agent uses each unimodal signal twice in each trial ("alpha + alpha" and "LF/HF + LF/HF"). Fig. 3 compares the results from these two conditions with the "alpha + LF/HF" condition, showing a smaller distance for the multimodal condition.

In Fig. 4, we show the distance of the "alpha + LF/HF" condition by varying σ of the alpha activity. From this figure, we observe that the smaller σ is, the more adequately the sound presentation is performed. Importantly, there is only a small difference in the distance between 30 and 40, whereas there is a large difference between 20 and 30.

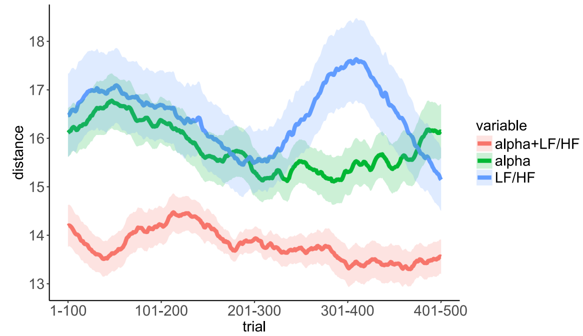

Figure 2. Average and standard error for each set of 100 trials for the distance between user's stress value and the baseline through 50 simulations (red line: alpha activity + LF/HF, green line: alpha activity only, and blue line: LF/HF only).

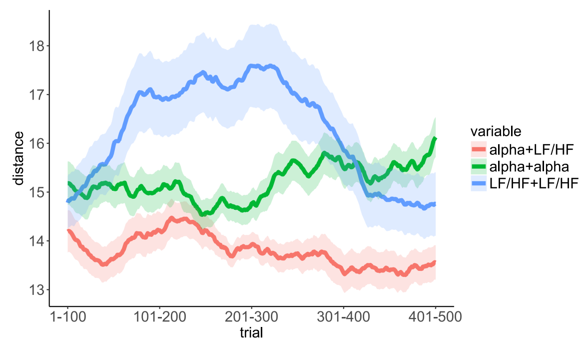

Figure 3. Average and standard error for each set of 100 trials for the distance between user's stress value and the baseline through 50 simulations (red line: alpha activity + LF/HF, green line: alpha activity + alpha activity, and blue line: LF/HF + LF/HF).

DISCUSSION

The previous section presents several important findings for the future research. The first finding is the advantage of using multimodal biological signals. So far, the past studies have demonstrated the effectiveness of multimodal biological signals for the estimation of emotion and stress state [5][8]. Consistent with such experimental studies, our simulation study used probabilistic distributions to represent different biological signals, indicating the superiority of observing multimodal biological signals. Especially, our study suggests that multimodal biological signals were better at helping the agent estimate the stress state than several observations of unimodal signals (Fig. 3). This result indicates that multimodal biological signals covering different aspects of a common source are complementary to each other, suggesting that the selection of the type of biological signals is important in designing an effective training system.

The second important finding is related to the verification of the intensity of noise in biological signals that can be accepted by the system. In experiments with human participants, it is impossible to manipulate such a hypothetical biological parameter directly. In contrast, in a simulation experiment, every parameter is explicitly defined, and the degree of noise allowed by the system operation can be verified (Fig. 4). With

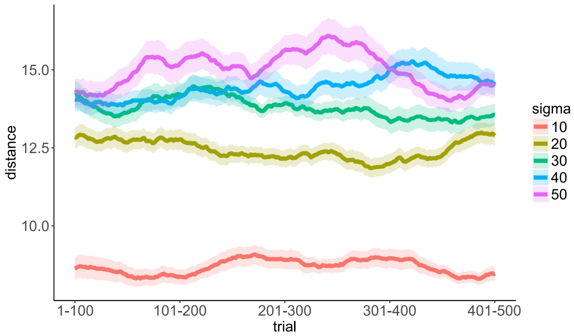

Figure 4. Average and standard error for each set of 100 trials for the distance between user's stress value and the baseline through 50 simulations according to the five kinds of normal distribution (σ =10, 20, 30, 40, and 50) of alpha activity.

this verification, it is possible to estimate the degree of performance, which is required for selecting the measurement device for the biological signals. Moreover, the cost of the measuring device can be reduced and the subject experiment can be performed with a design suitable for practical use.

However, there are many limitations in this research. The biological signals are arbitrarily mapped to probabilistic distributions. The user model also does not have any learning ability; it only changes the stress state as a reaction to the perceived sounds. Therefore, based on the findings in this experiment, we need to perform an experiment with human participants to confirm the findings of this research.

CONCLUSION

In this research, we developed a sound presentation agent using reinforcement learning and multimodal biological signals that provide adaptive training according to the user's stress state with stochastic observation. In addition, we verified the superiority of using multimodal biological signals through simulation, and evaluated the system as a preparation stage for subject experiment. In future, we will conduct subject experiments based on the results of this research, and compare those results with the simulation results in order to confirm the validity of the simulation.

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