Indoor environment control method for improving well-being using human thermal stress estimated by Yuragi learning

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***Abstract*—“Workstyle Reform” is promoted in Japan to improve the work environment surrounding workers. However, it is pointed out that the reduction of working hours by improving marginal productivity may increase workers’ stress on a per-unit hour basis. The realization of a system that quantifies stress and improves it accordingly will lead to our well-being, and in this paper, we propose methods that estimate the stress state of each individual and control the indoor environment in real time based on the estimated stress state to maintain or improve a well-being space. Estimation of the individual stress state is based on “Yuragi learning,” which is a method of making decisions from information including noise, based on a model of the cognitive process of a human brain. We implemented Yuragi learning to realize real-time stress estimation based on data streaming from biometric sensor devices. We also implemented the method to control devices that act in an indoor space on the basis of the estimation. In our experiment, we prepared two room conditions with different temperatures and humidity levels and confirmed that our method estimated the stress state of a subject and controlled the room with an actuator that directs the air flow to the subject in a real-time manner.**

***Index Terms*—Bayesian attractor model, biometric information, multi-modal integration.**

I. Introduction

In many countries, including Japan, the working environment surrounding workers is undergoing a reevaluation due to the decline in the working-age population caused by the falling birth rate and the aging population, as well as the diversification of working needs, such as balancing work with childcare and nursing care. As seen in the “Workstyle Reform” of Japan, long working hours are being rectified and in response to the spread of the new coronavirus, work at home and other work styles that accommodate an individual’s work-life balance are being recommended [1].

In terms of changes in workplace and work-related circumstances, the authors of [2] argue that the dominant models within human resource management theory and research mainly focus on ways to improve productivity, therefore risk affecting work-related well-being, and have detrimental consequences for employees and, in some cases, the organization. There is still room to consider ways of working that increase productivity while also taking into account personal well-being [3]. Hence, quantitative methods are required to assess individual stress for this, but even in the field of mental health, which is highly related to human stress, assessment methods have been developed for depression and other mental health problems.

Reference [4] takes the approach of providing an appropriate working environment to the challenge of increasing productivity. This study reported that workers who felt drowsy were awakened by air and light, and their productivity increased. If human stress can be estimated quantitatively, it would be possible to improve overall productivity from various perspectives, such as alleviating stress by manipulating the work space based on the estimation or directly encouraging people to take a break. The authors of [5] provide a survey of internal office spaces and well-being, and point out that while internal office spaces that provide workers with well-being are important, the scientific basis for such spaces needs further analysis.

It has been reported that it is possible to estimate an individual’s stress state using biometric information such as skin potential activity, skin temperature, and pulse wave [6]. By estimating a person’s stress state based on biometric information and manipulating the indoor environment accordingly, it may be possible to improve the stress of people spending time in a room. However, there are a few issues that need to be resolved. First, the biological information obtained from

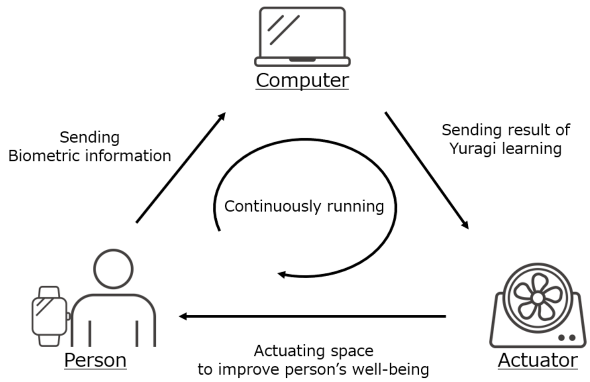


Fig. 1. System overview

wearable sensors contains noise. Furthermore, the impact of stress on biological information differs from person to person.

In this paper, we propose a method that estimates the stress state of each individual. Regarding the noise issue, we utilize "Yuragi learning," which is based on the cognitive mechanism of the brain to make decisions from observed information that contains noise. Our research group has applied it successfully in various studies so far [7]. Observation and decision-making processes in Yuragi learning are based on the Bayesian attractor model (BAM) [8]. The issue of individual differences is solved by implementing a personalized Yuragi learning training process and a multimodal integration process. We also propose a method to control the indoor environment based on human stress estimated by the method to maintain or improve a well-being space in which each individual can spend time comfortably and willingly for work. Our proposal is to sequentially estimate the stress state using biological information as input and control the indoor environment, and can be applied in various ways by changing the devices.

We conduct experiments to verify the series of operations in which our methods estimate the thermal stress state using a wristband capable of measuring biometric information and control a circulator based on the stress state. If the results indicate that a person is under thermal stress, the circulator control is applied to eliminate the cause of thermal stress or improve well-being.

II. Proposal

Well-being is a subjective indicator and varies from person to person. Therefore, in this study, we will use a method that senses various biological information using biometric sensors and estimates a person's psychological state from the obtained biometric information. Based on the estimation results, we will intervene in the space by controlling actuators and control the space to relieve the stress state to realize a well-being space where each individual can work spontaneously without feeling discomfort.

Here, we describe Fig. 1 and the structure of this section. First, biometric information is acquired (Sect. II-A). The biometric information obtained here is sent to the computer as streaming data. Before describing the stress state estimation method, BAM and Yuragi learning are explained in detail (Sect. II-B and Sect. II-C, respectively). The computer performs stress state estimation using Yuragi learning (Sect. II-D). Based on estimated stress information, the actuator acts on the indoor space (Sect. II-E).

A. Biometric information and its acquisition

Schmidt et al. provided a publicly available multimodal dataset for the researchers as WESAD (Wearable Stress and Affect Detection) [6]. This multimodal data set contains blood volume pulse (BVP), electrocardiogram (ECG), electrodermal activity (EDA), electromyogram (EMG), respiration (RESP), skin temperature (TMP), and 3-axis accelerometer (ACC) recorded from wrist and chest mounted devices on 15 subjects, as well as self-reported emotional states for three different emotional states (neutral, stress, amusement). Self-reported values for three different emotional states (neutral, stress, and amusement) were included. Based on these data, a large number of features (extracted from physiological and motion signals) and general machine learning methods (decision trees, random forests, AdaBoost, linear discriminant analysis, k-nearest neighbor methods) were used to create benchmarks. Using this information, the three-class (normal, stressed, and agitated) or two-class (stressed and unstressed) estimation problem yielded high-level estimation results, indicating that it is possible to estimate psychological states from multiple sources of biometric information.

B. Bayesian attractor model

In [8], the task of decision-making is to select one of multiple choices based on observed information, and a probabilistic framework is proposed in which the decision-making process is formulated by Bayesian inference. To model the decision-making process in the brain, a dynamics model is defined in which the variables representing the decision have attractors, and each of the aforementioned choices is associated with an attractor. Bayesian attractor model (BAM) uses Bayesian estimation with external stimuli as input to determine which of the previously prepared choices the observed target corresponds to.

In BAM, the probability distribution of the decision state z_t is updated using Bayesian inference when BAM receives input x_t. The posterior probability distribution $P(z_t|x_t)$ reflects the ambiguity and uncertainty of brain states. In this Bayesian inference, the following generative model is assumed.

$$z_t - z_{t-\Delta t} = \Delta t f(z_{t-\Delta t}) + \sqrt{\Delta t} W_t \tag{1}$$

$$x_t = M\sigma(z_t) + v_t. \tag{2}$$

Here, $f(z)$ represents *Hopfield dynamics*, which is one of the attractor models. f is designed to have N attractors, denoted by $\Phi = \{\phi_1, \ldots, \phi_N\}$, and N corresponds to the number of choices to be stored in the model. $M = [\mu_1, \ldots, \mu_n]$ is a matrix of feature values corresponding to each stored choice. σ is a multidimensional sigmoid function whose value range is 0 to 1. W_t and v_t are noise terms, $W_t \sim \mathcal{N}(0, \frac{q^2}{\Delta t} I)$ and $v_t \sim \mathcal{N}(0, r^2 I)$ respectively (I is the unit matrix). $\mathcal{N}$ means normal distribution. Since q and r determine the magnitude of uncertainty of the dynamics and the observation in the generative model, q is called *dynamics uncertainty* and r is called *sensory uncertainty*.

By estimating the aforementioned generative model in the reverse direction by Bayes' theorem, a model of decision making is obtained. To account for the non-linearity of the generative model, an approximate calculation is performed using the unscented Kalman Filter (UKF). This estimation of the state yields the posterior probability distribution $P(z_t|x_t)$ of z_t. Therefore, the attractor to which the internal state of the brain is close to is determined based on the size of the probability density $P(z_t = \phi_n|x_t)$. $P(z_t = \phi_n|x_t)$ is called "confidence" for the nth choice and decisions are made based on the magnitude of confidence. Even if the observed values contain noise, the accumulation of observations can increase confidence and enable appropriate decision-making.

C. Yuragi learning

Our research group has proposed a machine learning method for decision making based on BAM as Yuragi learning, and has successfully applied it to various applications [7]. The human brain is capable of performing complex cognitive and task functions simultaneously. The secret of this brain is believed to lie in the fluctuations (called "Yuragi" in Japanese) that exist in all living systems, including the human brain. Biological systems can have a high degree of freedom by utilizing noise rather than eliminating it. BAM is one of the models of human decision-making proposed to explain reaction times, correct response rates, and changes in decision making in decision-making experiments. Yuragi learning is a framework for engineering applications of BAM, providing design of observations (preprocessing), design of attractors (training), and ties between decision-making and various estimation problems.

D. Stress estimation by Yuragi learning

Figure 2 provides an overview of our stress estimation method in which we create discriminators using Yuragi learning. We extract features from the information observed in each modality. We denote the observation of the ith modality by $o_t^{(i)}$ and the features extracted from $o_t^{(i)}$ by $x_t^{(i)}$. $x_t^{(i)}$ is used as input to the corresponding discriminator based on Yuragi learning. Each discriminator updates its cognitive state $z_t^{(i)}$ using feature inputs $x_t^{(i)}$ for the ith modality. $F_i = P(z_t^{(i)} = \Phi|x_t^{(i)})$ is the output of the discriminator, and our method makes the final decision by integrating F_i for all modalities.

Yuragi learning is a method that makes decisions after accumulating a sufficient amount of observations, and is characterized by being less susceptible to temporary noise. Therefore, we address the noise in biometric information using Yuragi learning. We also take into account individual differences by configuring the discriminators for each person. Training in Yuragi learning simply sets the features corresponding to stress/non-stress states to its feature matrix M. Therefore, it is possible to easily train a classifier for each individual. Additionally, the useful modalities are also distinct for each person. Therefore, we also select the useful modalities for each person using the confidence level of Yuragi learning. The estimation results with high confidence level are used for the final decision. By doing so, we can avoid using results that cannot differentiate the stress state in the current situation.

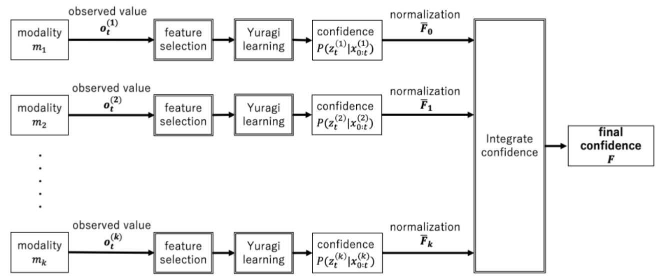


Fig. 2. Stress estimation model of the proposed method

1) Training: Training dataset requires biometric information labeled to represent various states. In this paper, we use the label "stress" to represent the state of stress and the label "non-stress" to represent the state of not feeling stress.

a) Feature selection: This section explains the process of selecting features. The candidate selection process begins after collecting some observations. We denote the set of time slots T^{train} in which observed data can be used for training. Candidate features are selected by the following steps.

- To begin, we include all the features in a candidate feature set.
- Normalize the features by

$$x_{t,j} = \frac{x_{t,j}^{cand} - \mu_j}{\sigma_j} \tag{3}$$

  where $x_{t,j}^{cand}$ is the jth feature in a candidate feature set at time t. μ_j is the mean, and σ_j is the standard deviation of the jth feature where the label is "non-stress."
- Calculate $\bar{x}_j$, which is the average of $x_{t,j}$ in the case of stress state,

$$\bar{x}_j = \frac{\sum_{\{t \in T^{train}, L(t)=stress\}} x_{t,j}}{\sum_{\{t \in T^{train}, L(t)=stress\}} 1} \tag{4}$$

  where $L(t)$ is the label of the dataset at time t.
- Check if the magnitude of each element of $\bar{x}_j$ is greater than the threshold λ. If $|\bar{x}_j|$ is greater, keep the jth feature as a candidate feature. Otherwise, the jth feature is excluded.

For each individual, the same process is repeated for each modality. Note that if $|\bar{x}_j|$ is smaller than the threshold for all j in a modality, the modality itself is excluded. Through these steps, we can identify features that can differentiate between a stress and a non-stress state.

b) Setting of attractor: Discriminators based on Yuragi learning can be trained by assigning typical features of labels to attractors. We set the typical features of the non-stress state to ϕ_0 and those of the stress state to ϕ_1.

2) Multimodal stress estimation: The initial normalized features x_t are derived from the observation information using Eq. (3). Subsequently, the decision state is estimated using a Bayesian approach based on the generative model expressed in Eqs. (1) and (2), and then the confidence level $P(z_t|x_t)$ is calculated. As shown in Fig.2, there is a discriminator for each modality, each of which estimates the stress state. The results of each discriminator are then combined to make the final decision through the following steps.

- Creation of confidence vectors
  We construct a confidence vector that includes the confidence calculated from each discriminator. The confidence vector for the ith discriminator is obtained by
  $$F_i = P(z_t^{(i)} = \Phi | x_t^{(i)}) \quad (5)$$
- Exclusion of results with low confidence
  Some discriminators may not be able to distinguish the stress state. In such cases, the confidence of the discriminator becomes low. In our method, we exclude the results of discriminators whose confidences are less than a pre-defined threshold.
- Integration of confidence vectors
  We integrate the confidence vectors of the selected discriminators. The method to calculate the weighted sum of confidence vectors is used.
  $$F = \frac{\Sigma_{i \in \mathcal{M}} w_i \bar{F}_i}{\Sigma_i w_i} \quad (6)$$
  where $\mathcal{M}$ is the number of modalities, F is the final result after integration, and w_i is the weight for the ith modality. $\mathcal{M}$ is determined by the process excluding low-confidence modalities and the process described in Sect. II-D1. $\bar{F}_i$ is the normalized confidence vector obtained by
  $$\bar{F}_i = \frac{F_i}{\sum_{j \in \mathcal{M}} F_j} \quad (7)$$
  Note that w_i needs to be defined in advance. In this paper, we assume that w_i is trained using the data of the subjects so as to maximize the accuracy of the final decisions F. Then, common w_i can be used for all subjects.

The estimation of stress state using biometric data has been tested on 31 subjects to confirm its validity in our preliminary experiment. This paper presents the realization of a framework for automatic control of the indoor environment using biometric data, and for reasons of space limitation, we omit the detail of the result.

E. Control of actuator

Various approaches targeting a person's five senses can be considered to control actuators to maintain a sense of well being in the indoor space. For example, music could be played to encourage a break when strong stress is estimated, or an aroma diffuser could be used to spread the person's preferred scent in the space. In this paper, we implement a specific example of stress reduction in a thermal environment through the use of air conditioning equipment. Details are given in the next section.

Fig. 3. E4 wristband [9]

Fig. 4. Daikin assist circulator [10]

III. Evaluation

A. Implementation

In the experiment, we consider the discomfort felt when the temperature and humidity in a room are set to values that would be perceived as uncomfortable, and show that the proposed system can estimate such stress and control the actuators in real time.

1) Devices: We use the E4 wristband (Fig. 3) [9] to acquire biometric information, which is also used in [6], manufactured by Empatica. The E4 wristband can acquire 3-axial acceleration (ACC), blood volume pulse (BVP), electrodermal response (EDA), heartbeat interval (IBI), and skin temperature (TMP).

In order to relay the biometric information obtained from the E4 wristband to the computer that performs Yuragi learning, we installed a streaming server provided by Empatica. The streaming server software is installed on a laptop computer and connected to the E4 wristband via Bluetooth. The streaming server is capable of acquiring biometric data from multiple E4 wristbands and transmitting the data over the network using the APIs provided by Empatica. Note that observed data are also stored on the wristbands, and if communication is temporarily interrupted, it has the ability to resend the data it was unable to send when reconnected.

For an actuator to control an indoor room, we use a Daikin assisted circulator (Fig. 4) [10]. In addition to the airflow adjustment function, this device has the function of adjusting the airflow direction. The assist circulator is connected to a small Linux-based computer (we used a Raspberry Pi3 model B, hereinafter abbreviated as PI3) via serial communication. We have made hardware modifications to the assisted circulator so that its operation can be changed by serial commands sent from the PI3. In the implementation in this experiment, the estimation of the stress state by Yuragi learning is performed on a computer that runs the streaming server, so this computer sends control commands to the assist circulator via the PI3.

2) Feature extraction: Stress state estimation using Yuragi learning is performed on the computer where the aforementioned streaming server is installed. The stress estimation software using Yuragi learning and the streaming server software communicate with each other through socket communication using TCP. In this implementation, the Yuragi learning software connects to *localhost* with a specified port. By specifying in advance the type of biological data to be acquired by the streaming server, the biological data arrive at the socket as streaming information.

In this implementation, we obtain four types of biometric information, TMP, EDA, BVP, and IBI from an Empatica E4 wristband. That is, the number of modalities is four. In addition to the raw EDA observations recorded by Empatica E4, we extract three key values from the recorded EDA by using cvxEDA [11], phasicEDA, SNMAphasicEDA and tonicEDA. A brief description follows.

- phasicEDA: Signal R, which is extracted only from the part of EDA that changed abruptly in a short period of time
- SNMAphasicEDA: Changes in the calculated periodicity of R
- tonicEDA: Signal with slowly changing trend taken out

For each of the above total of seven observations, the mean, standard deviation, minimum value, maximum value, range, and slope are calculated for a fixed time. These 7×6 values are used as feature values. We used a sliding window with a window size of 60 seconds and a window shift of 0.25 seconds.

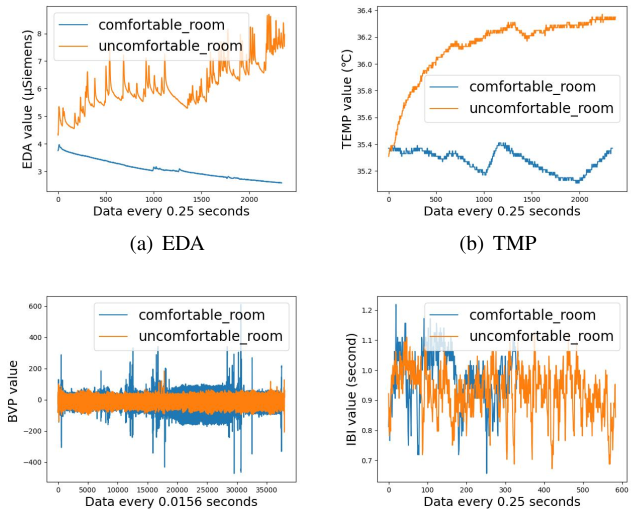
3) Yuragi learning: Although the software of Yuragi learning is available in [12], multimodal processing functions have not been implemented, and from the viewpoint of real-time calculation, we implemented it in the C++ language. The basic feature of Yuragi learning written in the C++ language is published in [13].

We set the threshold λ to 1.1 for the selection of features. We also set the threshold value for the confidence obtained by Yuragi learning to 0.001. The sensory uncertainty r is set to 0.4 and the dynamics uncertainty q is set to 0.5. These values were selected from those that were highly effective in the pre-training data.

B. Experimental setup

To conduct experiments for the validation of the proposed system, we prepared comfortable and uncomfortable indoor rooms based on PMV (Predicted Mean Vote) as defined in ISO 7730 [14]. PMV is a famous index intended to predict the average value of a group of occupants' votes on a seven-point thermal sensation scale (Hot $(+3)$ to Cold (-3)). In this experiment, the PMV of the comfortable room was set to 0 and that of the uncomfortable room to $+2$.

Training data is acquired in each room for one subject. When acquiring the data, an interval of 10 minutes is set to avoid the influence of the previous environment, and then the data is acquired for 10 minutes. After the learning is complete, the subject moves to a room with an uncomfortable environment and stays for 10 minutes. Yuragi learning is performed for each biological information every second. The results of the estimation are checked every 10 seconds, and if the stress state is estimated as an estimation result more than a certain number of times, the room environment is changed by an actuator (assisted circulator). This experiment is designed to show that it is possible to demonstrate that the implemented system can estimate discomfort due to temperature and humidity and control the equipment to remedy the situation in real time.



(a) EDA (b) TMP

(c) BVP (d) IBI

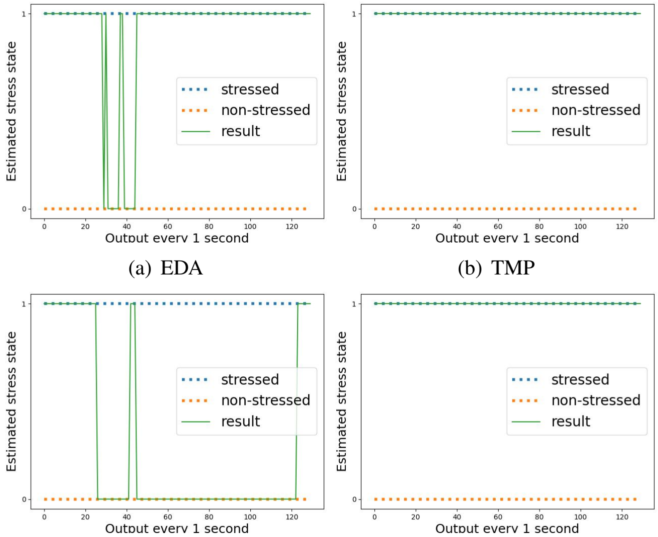
Fig. 5. Observed raw data from E4 wristband

C. Result

We have confirmed that control occurs as expected. The input during training in each room is shown in Fig. 5, and the results of feature selection based on these inputs are shown in Table I for the subject. The blue and orange lines represent the measured values for 10 minutes spent in the comfortable and uncomfortable rooms, respectively, where the number of samples that can be obtained per unit of time differs according to the Empatica E4 specifications.

The estimation results for each biometric information are shown in Fig. 6, and the integrated result is shown in Fig. 7. Note that the actual output of Eq. (6) is the confidence level in two attractors (ϕ_0 corresponding to the non-stressed state and ϕ_1 corresponding to the stressed state), but the estimated state of each time step is shown in the figure. The solid green line is the result of the estimation.

We have succeeded in estimating the stress state of the subject in the uncomfortable room, as shown in Fig. 7. The air blowing of the circulator continued during the stress state. Although subjective comfort was somewhat improved by the airflow provided by the circulator, this was not seen as a biological response. In the future, further experimental evaluations will be conducted with different environmental settings and actuators.



(a) EDA (b) TMP

(c) BVP (d) IBI

Fig. 6. Stress estimation result (0: 'non-stressed state' and 1: 'stressed state')

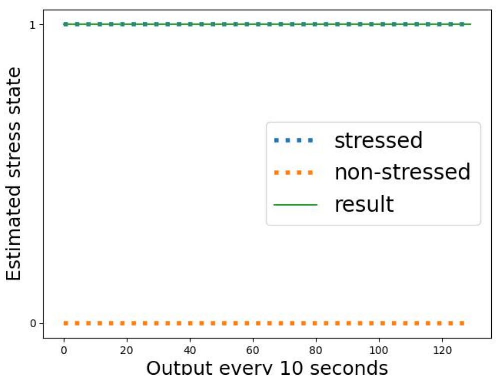


Fig. 7. Multimodal Integration of stress estimation

IV. Conclusion

We proposed a method for estimating stress by integrating multiple types of biometric information using Yuragi learning. In our method, we configure multiple discriminators based on Yuragi learning. Each discriminator makes decisions based on the corresponding biometric information. Then, by integrating the decisions of all discriminators, our method makes the final decision. Furthermore, our method also excludes decisions of Yuragi learning whose output confidence is low to avoid estimation of stress from inaccurate information. Experiments have shown that the system can operate in real time from observation of actual biological data to control of actuators. A future work will be to clarify how to control the actuators to completely remove stress and how to estimate and control them for different people.

TABLE I
Selected Features

EDA	mean	std	min	max	range	slope
phasicEDA						
SNMAphasicEDA						
tonicEDA						
TMP	mean		min	max		
BVP		std	min	max	range	
IBI	mean	std		max	range	slope

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