Master's Thesis

Title

Real-time stress detection using Yuragi learning by multimodal integration of living-body information

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Abstract

In recent years, psychological fatigue based on the working environment and mental strain has become an issue. Even short-term mental burdens can become long-term and persistent stresses if such burdens are accumulated. To avoid such situations, rests are important; By resting the body and mind, the mental load can be reduced. By detecting mental stress in real time, we can urge people to take a rest. The living-body information is useful to detect mental stress. The sympathetic nervous system becomes dominant in a state of stress, which causes biological reactions. Such biological responses can be estimated from living-body information obtained by using wearable sensors. A wearable sensor can observe various types of living-body information such as body temperature, skin electrical activity, and heart rate, which have a significant correlation with the state of mental load. That is, such living-body information can be used to detect mental stress. Especially, combining multiple information is one of the promising approaches for accurate detection of mental stress. However, such living-body information measured by wearable devices contains noise. In addition individual differences exist in such living-body information. Therefore, the real-time stress detection should handle such noise and individual differences.

In this thesis, we propose a real-time stress detection method that can handle noise included in the monitored information and the individual differences. Our approach is based on "Yuragi learning" and multimodal integration. Yuragi learning is a method to make real-time decisions from information including noise, based on a model of the cognitive process of a human brain called the Bayesian Attractor Model (BAM). Yuragi learning makes decisions on which of predefined options matches the current state by continuously updating the cognitive state every time new observations are obtained.

In our method, we configure multiple discriminators based on Yuragi learning. Each discriminator makes decisions based on the corresponding information. Then by integrating the decisions of all discriminators, our method makes final decision in real time. In this method, the information used to make final decisions should be carefully selected, because the impact of stress on living-body information is different from person to person. Therefore, our methods select the information for each person and exclude the information that cannot distinguish the stress state. In addition, our method also exclude the decisions of Yuragi learning whose outputted confidence is low to avoid the detection of stress from inaccurate information. In this thesis, we demonstrate that our method detect stress states accurately through experiments. In this experiments, we use the data obtained by subject experiments where living-body information and reports on subjective stress level are obtained. The results show that our method can detect stress accurately, while the methods without selecting modalities and without avoiding using results with low confidence cause false negatives and false positives.

Keywords

Real-time stress detection

Yuragi learning

Bayesian attractor model

Multimodal integration

Living-body information

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1 Introduction

In recent years, psychological fatigue based on the working environment and mental strain has become an issue. Nowadays, there are many situations in which people feel stress at work and in their daily lives. Stressors that cause stress can be classified into three categories: 1) physical stressors such as heat, cold, noise, and congestion, 2) chemical stressors such as pollutants, drugs, oxygen deficiency or excess, and carbon monoxide, and 3) psychological and social stressors such as personal relationships, work problems, and family problems [1]. These stressors affect psychological, physical, and behavioral aspects. Even short-term mental burdens can become long-term and persistent stresses if such burdens are accumulated.

Examples of physical impacts include heat stroke, cooling sickness, and autonomic nervous system disorders. Methods to reduce the risk of heat stroke include using home air conditioning, spending more time in air-conditioned areas, and living in dwellings with ample shade from trees and shrubs have been advocated [2]. This suggests that in the working and living environment, it is important to rest the body and mind and reduce the mental load before it seriously affects health.

The sympathetic nervous system becomes dominant in a state of stress, which causes biological reactions. Therefore, research focusing on the relationship between living-body responses and stress has been conducted. Among them, research on stress estimation using living-body information that can be obtained from wearable devices has been active. There are various types of living-body information that can be obtained from wearable devices, and research is being conducted on living-body information that is significant for stress.

Sets et al. demonstrated that stress detection with accuracy of 82.8% can be achieved in the workplace by monitoring the biometric skin electrical activity (EDA) using a wearable device [3]. This results indicate that stress and skin electrical activity are significantly correlated. Betti et al. proposed a method to detect stress based on each of the three living-body information (EEG(Electrocardiogram), EDA(Electrodermal activity), and EEG(Electroencephalogram)) [4]. They found high significant correlation with stress in the 15 features extracted from the living-body information.

Combining multiple information is one of the promising approaches for accurate detection of mental stress. Schmidt et al. provided multimodal dataset for the researchers on stress detection with the demonstration that the integration of multiple information can improve the accuracy of the stress detection [5].

However, while the use of wearable sensors enables real-time data acquisition of living-body information that can be used to determine the stress state, the living-body information acquired by wearable sensors contains noise. Therefore, in order to determine the stress state in real time, a method that can handle such noise is neccessary.

In addition, individual differences exist in living-body information; the impact of stress on living-body information is different from person to person. Therefore, the real-time stress detection should also handle individual differences.

Our research group has proposed a method called Yuragi learning [6]. Yuragi learning is a cognitive method based on the Bayesian Attractor Model (BAM) [7], which models the cognitive processes of the brain to make decisions from observed information with noise. In this method, the cognitive state of the brain is treated as a random variable. Then, the decision-making state is updated by Bayesian estimation each time an externally observed value is obtained. By repeating this updating process, this method can make decisions even if the information obtained at each time contains noise.

In this thesis, we propose a method to detect stress by integrating multiple types of living-body sensing information using Yuragi learning. In our method, we configure multiple discriminators based on Yuragi learning. Each discriminator makes decisions based on the corresponding information. Then by integrating the decisions of all discriminators, our method makes final decision in real time. In this method, the information used to make final decisions should be carefully selected, because the impact of stress on living-body information is different from person to person. Therefore, our methods select the information for each person and exclude the information that cannot distinguish the stress state. In addition, our method also exclude the decisions of Yuragi learning whose outputted confidence is low to avoid the detection of stress from inaccurate information.

The rest of this thesis is organized as follows. Section 2 explains the related work including stress detection and the Yuragi learning. Section 3 proposes a real-time stress detection method based on Yuragi learning and multi-modal integration. In Section 4, we evaluate our method. Finally, Section 5 concludes this thesis.

2 Related work

2.1 Recent research on stress detection

The sympathetic nervous system becomes dominant in a state of stress, which causes biological reactions. Therefore, researches focusing on the relationship between living-body responses and stress have been conducted. Among them, research on stress estimation using living-body data that can be obtained from wearable devices has been active.

There are various types of wearable devices, such as wristband devices [8] and wearable chest devices [9]. Smartphones are also important devices for stress detection; stress detection systems that can work with smartphones have also been developed [10, 11].

The information that can be obtained from such wearable devices includes a wide variety of living-body information. Thus, researches on living-body information that has significant correlation with stress have been conducted.

Sets et al. demonstrated that stress detection with accuracy of 82.8% can be achieved in the workplace by monitoring the biometric skin electrical activity (EDA) using a wearable device [3]. This results indicate that stress and skin electrical activity are significantly correlated.

Jebilli et al. investigated the relationship between stress and EEG for workers on construction sites [12]. They analyzed brain activity recorded by a wearable EEG device and showed that EEG has the potential to quantitatively measure human stress.

Some studies have also investigated the relationship between stress and multiple living-body measures. Betti et al. proposed a method to detect stress based on each of the three living-body information (EEG(Electrocardiogram), EDA(Electrodermal activity), and EEG(Electroencephalogram)) [4]. They found high significant correlation with stress in the 15 features extracted from the living-body information.

Combining multiple information is one of the promising approaches for accurate detection of mental stress. Schmidt et al. provided multimodal dataset for the researchers on stress detection with the demonstration that the integration of multiple information can improve the accuracy of the stress detection [5].

The above researches demonstrated the living-body information is useful for stress detection. However, living-body information measured by wearable devices contains noise.

In addition, individual differences exist in living-body information; the impact of stress on living-body information is different from person to person. Therefore, the real-time stress detection should handle noise included in the measured data and individual differences.

In this thesis, we propose a real-time stress detection method that handles noise included in the measured data and individual differences by integrating multiple types of living-body sensing information using Yuragi learning.

2.2 Yuragi learning

Yuragi learning [6] is a cognitive method based on the Bayesian Attractor Model (BAM) [7], which models the cognitive processes of the brain to make decisions from observed information with noise.

In the BAM, a cognitive process of a human brain to make decisions on which of predefined options called *attractors* matches the current state is modeled as follows. The brain obtains observations and abstract them. Hereafter, we denote the abstracted observation at time t by x_t. The cognitive state of the brain is treated as a random variable. We denote the cognitive state at time t by z_t. z_t is updated each time x_t is obtained by using the following generative model.

$$z_t - z_{t-\Delta_t} = \Delta_t f(z_{t-\Delta_t}) \sqrt{\Delta_t} w_t \tag{1}$$

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

where $f(z)$ represents the Hopfield dynamics. w_t and v_t are Gaussian noise variables. $M = [\mu_1, ..., \mu_s]$ and μ_i is the observation value corresponding to the state ϕ_i. σ is a multidimensional sigmoid function.

The above generative model is nonlinear. Bitzer et al. used the Unscented Kalman filter (UKF) to update the cognitive state.

By the above steps, the brain obtains the cognitive state $P(z_t = \phi_i \mid x_{0:t})$ at time t where $x_{0:t} = x_1, ..., x_t$. We call $P(z_t = \phi_i \mid x_{0:t})$ the confidence. In the BAM, if the confidence on an option exceeds the threshold λ, the brain make a decision.

Yuragi learning is a method for a computer to recognize a situation based on the BAM. In Yuragi learning, first, S attractors and μ_i observed values corresponding to each attractor are defined. Then, each time new observations are obtained, we calculate the abstracted observation x_t and update the cognitive state by using x_t. If $P(z_t = \phi_i \mid x_{0:t})$ exceeds the threshold λ, the current situation is recognized as i.

3 Real time stress detection by Yuragi learning and multimodal integration

In this thesis, we propose a method for real-time detection of stress state using multiple living-body information. This method should handle the following problems; (1) Noise: information obtained by wearable sensors includes noise, (2) Individual difference: the impact of stress on living-body information is different from person to person, and (3) Situation: the living-body information that is useful for making decisions depends on the situation. In this section, we propose a method to handle all of the above problems.

3.1 Overview

Figure 1 shows the overview of our real-time stress detection method. In this method, we use k modalities. For each modality, we extract the features from the observed information. We denote the observation of ith modality by $o_t^{(i)}$ and features extracted from $o_t^{(i)}$ by $x_t^{(i)}$. The extracted features are used as inputs of corresponding discriminator based on Yuragi learning. Each discriminator updates its cognitive state by using the inputted features. That is, the cognitive state of discriminator of ith modality $z_t^{(i)}$ is updated by using $x_t^{(i)}$. The output of discriminator is $F_i = P(z_t^{(i)} \mid x_{0:t}^{(i)})$. By integrating F_i for all modalities, our method makes final decision.

In this method, we handle the noise included in observations by using Yuragi learning. The discriminator based on Yuragi learning continuously update its cognitive state each time new observations are obtained. By repeating updating the cognitive state, the discriminator can make decisions even if the observation includes noise.

We handle individual differences by configuring the discriminators for each person. The discriminator based on Yuragi learning can be trained just by setting the features corresponding to the state. So, we can easily train the discriminator for each person even if we have only a limited amount of observations for each person. In addition, the useful modalities are also different from person to person. Therefore, we also select the useful modalities for each person by using the observations for each person.

In this method, the results of discriminators used for final decision are also selected for the situation, because the living-body information that is useful for making decisions depends on the situation. In this method, we integrate only the results with high confidence to make final decision. By doing so, we can avoid using the results based on the modalities that cannot distinguish the stress state in the current situation.

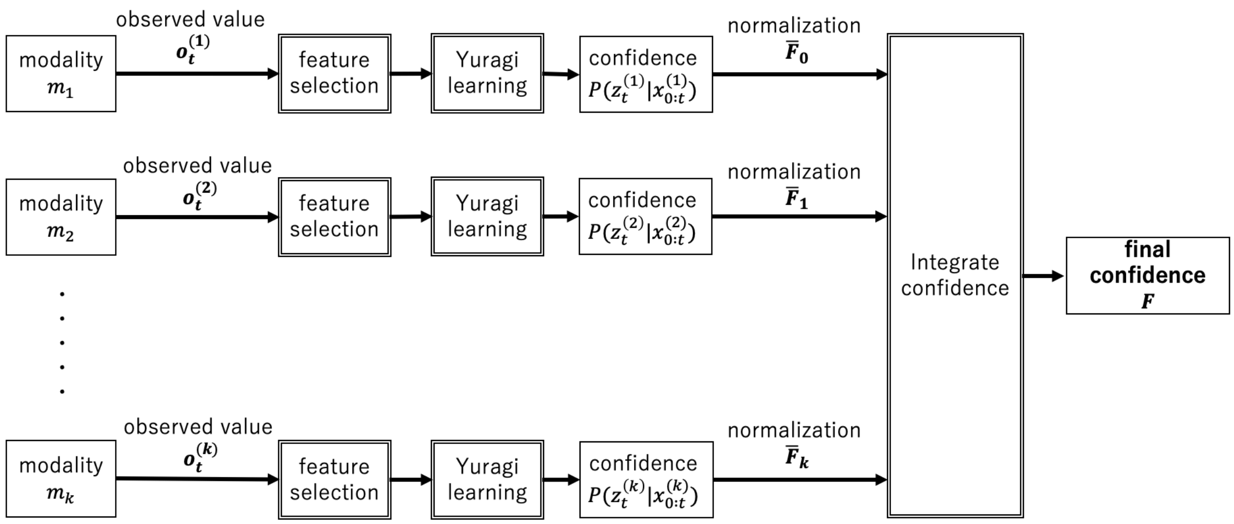


Figure 1: Stress detection model of the proposed method

3.2 Training

3.2.1 Feature selection

In our method, features used by the discriminator of each modality are selected for each person. If no suitable features are selected, the modality is not used in our method. The rest of this subsection explains how to select features.

In our method, features are selected from candidates of the features. We can use the well-known features and the features extracted by using machine learning models as the candidate of features.

The feature selection is performed after obtaining some observations. The candidate features are calculated from the observations. We also denote the set of time slots T^{train} whose data can be used for training. By using the observations obtained in T^{train}, we select features by the following steps.

1. Normalize the candidate features by

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

where $x_{t,j}^{\mathrm{cand}}$ is the jth candidate of features obtained at time t, μ_j and σ_j is the mean and the standard deviation of the jth candidate of features in the case without stress.

2. Calculate the average of $x_{t,j}$ in the case of stress

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

where $L(t)$ is the label at time t.

3. Check if the absolute value of each element of $\bar{x}_j$ exceeds the threshold λ. If the absolute value of $\bar{x}_j$ is larger than the threshold, select the jth feature. Othewise, the jth feature is excluded

4. If all elements of $\bar{x}_j$ are smaller than the threshold, the modality itself is excluded.

The above procedure is performed for each modality for each person. By the above steps, we can select features that can distinguish the stress state.

3.2.2 Setting of attractor

The discriminators based on Yuragi learning can be trained just by setting the typical features corresponding to each label. In this thesis, we set the typical features in the case without stress to 0, and those in the case with stress to $\bar{x}$ which is constructed of $\bar{x}_j$ calculated in the above steps.

3.3 Stress detection

3.3.1 Process for each modality

We use the Yuragi learning to make decisions based on each modality. Each discriminator based on Yuragi learning works as follows. First, normalized features x_t extracted from the observation information o_t are obtained by Eq. (3). Then, the cognitive state is updated by Bayesian estimation based on the generative model represented by Eqs. (1) and (2) and the confidence $P(z_t|x_{0:t})$ obtained. By repeating the above steps, the discriminator make decisions on the stress state in real time.

3.3.2 Multimodal integration

After the result of each discriminator is obtained, we integrate them to make final decisions by the following steps.

Creation of confidence vectors We construct the vector indicating the confidence for each discriminator. The confidence vector for kth discrminator is obtained by

$$F_k = P(z_t^k \mid x_{0:t}^k). \tag{5}$$

Exclusion of cognitive 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. We avoid using the results of such discriminators. In this thesis, we exclude the results of discriminators whose confidences are less than a threshold.

Integration of confidence by weighted sums We integrate the confidence vectors of the selected discriminators. In this thesis, we use a simple method that calculates a weighted sum of confidence vectors.

$$F = \sum_{i \in M} \frac{w_i \bar{F}_i}{\sum_i w_i} \tag{6}$$

where M is the set of selected modalities, F is the final confidence result after integration, and w_i is the weight for the ith modality. $\bar{F}_i$ is the normalized confidence vector obtained by

$$\bar{F}_k = \frac{F_k}{\|F_k\|_1}. \tag{7}$$

Note that the weights w_i is required to be defined in advance. In this thesis, we assume that the common w_i can be set for all people, and we use w_i trained by using the data of the other subjects so as to maximize the accuracy of the final decisions F in our evaluation.

4 Evaluation

We evaluate our method by using the data obtained by a subject experiment. In this section, we explain the settings in our experiments and results.

4.1 Settings

4.1.1 Dataset

We use the data obtained in a subject experiment [13]. In this experiment, each subject stayed in a room where we changed the temperature and humidity. Each subject was asked his/her subjective well-being (SWB) levels every 30 seconds. SWB was reported as a number from 1 (uncomfortable) to 10 (comfortable). At the same time, living-body information of the subjects was recorded. We use the data recorded by using Empatica E4 wristband. Table 1 shows the living-body information recorded by Empatica E4. Though three-axis acceleration (ACC) was included the recorded information, we do not use the ACC because the ACC does not have correlation with stress.

In addition to the raw EDA observations recorded by Empatica E4, we extract an isotonic level called skin conductance level (SCL) and a phasic response called skin conductance response (SCR) from the recorded EDA by using cvxEDA [14]. We also extracted the same features for pituitary nerve activity (SNMA), which is considered to have the potential to estimate autonomic nervous system activity with superior performance compared to raw SCR.

Table 1: List of modalities of the acquired dataset

Sensor devices	Modality names	Details	Frequency
Empatica E4 (wrist)	ACC	3-axis acceleration	32
	EDA	ElectroDermal Activity	4
	TEMP	Temperature	4
	BVP	Blood Volume Pulse	64
	IBI	Inter-Beat Interval	-
	HR	Heart Rate	1

The subject experiment included 31 subjects. But the living-body information of 2 subjects was not successfully recorded. That is, we use the data for 29 subjects.Hereafter we define $Sub - i$ as the $i - th$ subject.

4.1.2 Label settings

We set the label (baseline or stress) based on the recorded SWB values. The recorded SWB values depend on subjects. For example, a subject may report 1 if he/her is uncomfortable while another subject may report 3 when he/her feels similarly. Considering such individual difference, we set the label based on the minimum value reported by each subject as showin in Table 2.

Table 2: Relationship between SWB and label

SWB	minimum value, second lowest value	other values
label	1	2
state	stress state	baseline state

4.1.3 Parameters

Candidate features We obtain candidate features from the observed values shown in Table 1. To extract features, we first extract the observations within a window by using the sliding window method with a window size of 60 seconds and a window shift of 0.25 seconds. Then, we extract the mean (mean), standard deviation (std), minimum value (min), maximum value (max), range of values (range), and slope (slope) for the observations within each window.

Parameter We set the threshold λ for feature selection to 1.1. We also set the threshold value for the confidence obtained by Yuragi learning to 0.001. We set the parameters of Yuragi learning method as shown in Table 3.

Table 3: Parameter list of BAM

Parameter name	variable	value
sensor uncertainty	s	0.4
dynamic uncertainty	q	0.5

4.2 Example of results of real-time stress detection

In our method, features used to detect stress are selected for each person. Table 5 and Table 4 shows the selected modalities and features for Sub-12 and Sub-06. As shown in this table, the selected modalities and features depends on subjects.

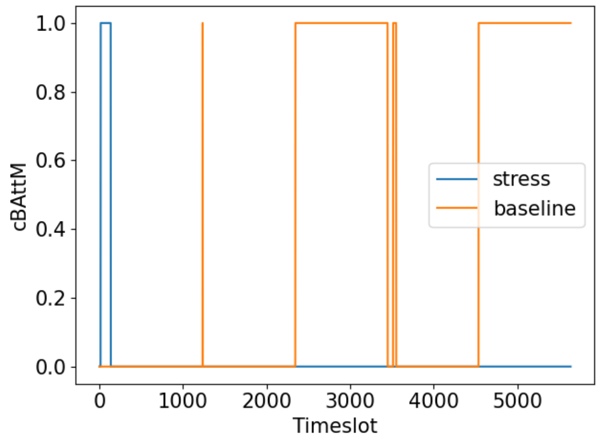
Table 4: Modalities and their features used for stress detection of Sub-06

modality	select feature
EDA	mean、std、min、max、range、slope
phasicEDA	std

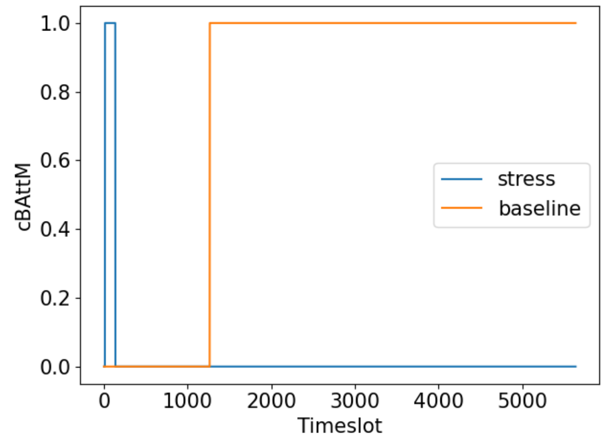
Table 5: Modalities and their features used for stress detection of Sub-12

modality	select feature
TEMP	mean、min、max
EDA	mean、std、min、max、range
HR	mean、min、slope
IBI	max

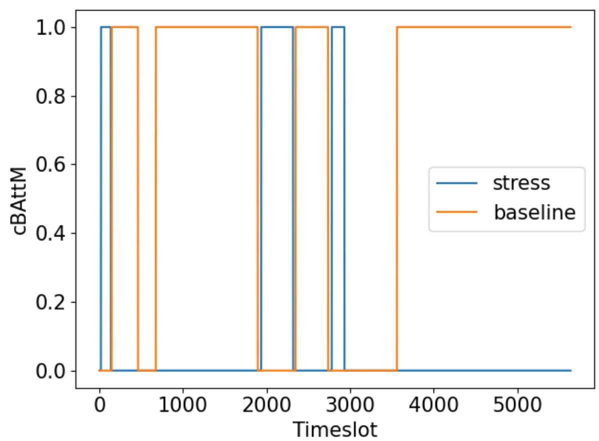
Figure 2 and Figure 3 show the results of real-time stress detection by our method. In these figures, we plot the normalized confidence by each discriminator and the integrated result. TEMP, EDA, HR, and IBI are selected as useful modality for Sub-12 by our method, while EDA and phasicEDA are selected for Sub-06. As shown in these figures, even when each discriminator cannot accurately detect stress, we can detect the stress accurately. For example, the discriminators based on HR and IBI mistakenly classify the state of baseline as the state with stress in some time slots. But by integrating the results of all discriminators, we can accurately classify the state in such time slots. In another example shown in Figure 3, the discriminator based on EDA cannot recognize the state with stress for Sub-06 in some time slot. But phasicEDA can identify the state in such time slot. By integrating these results, we can make accurate decisions.



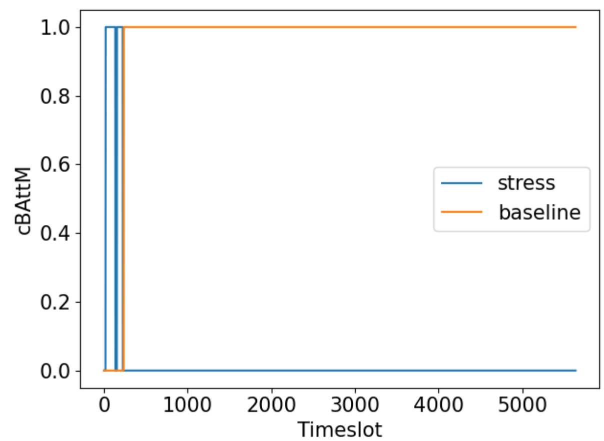
(a) Confidence in TEMP



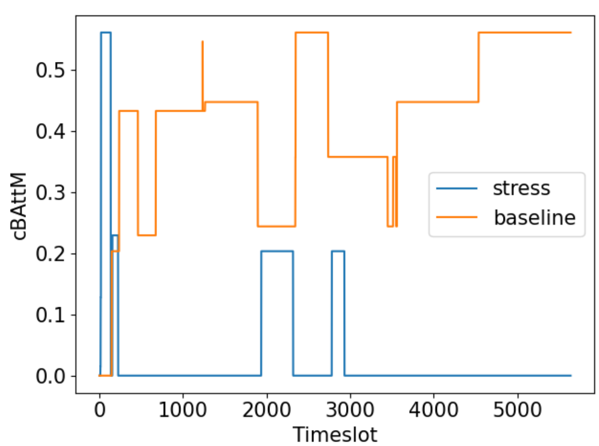
(b) Confidence in EDA



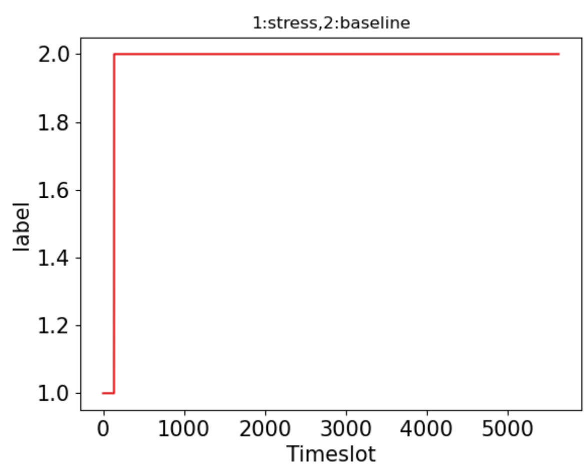
(c) Confidence in HR



(d) Confidence in IBI

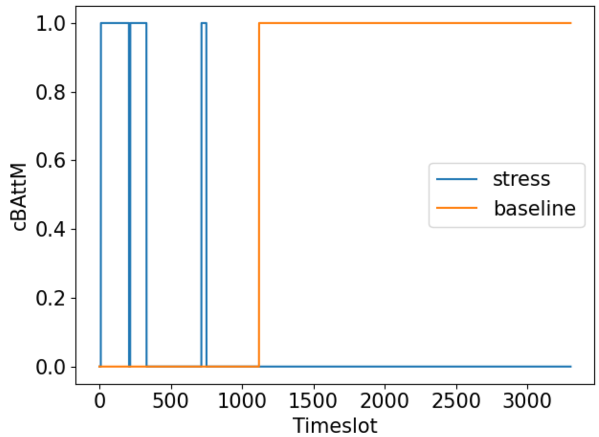


(e) Integration result

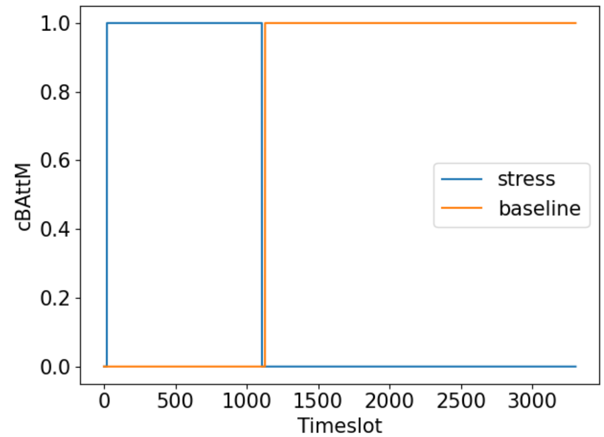


(f) Correct label

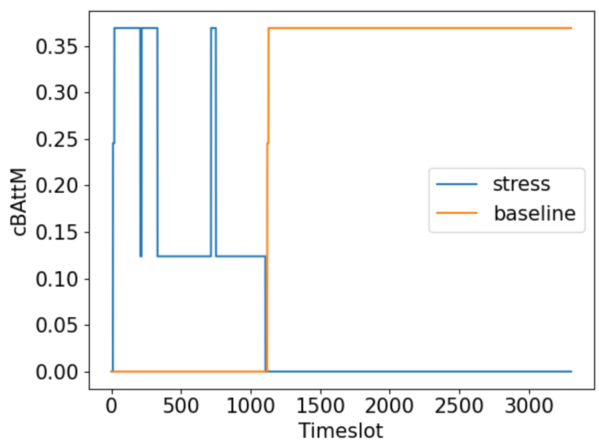
Figure 2: Sub-12 Results of the proposed method



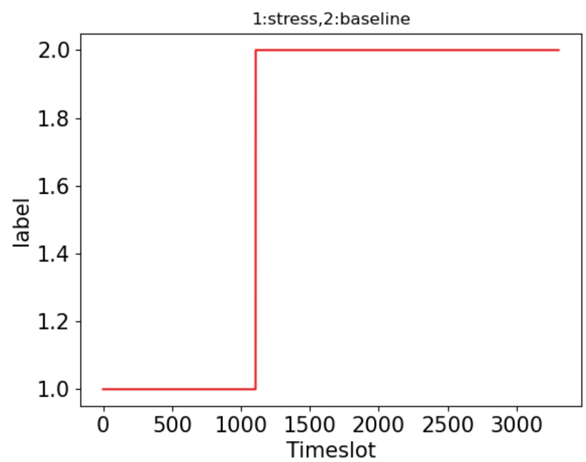
(a) Confidence in EDA



(b) Confidence in phasicEDA



(c) Integration result



(d) Correct label

Figure 3: Sub-06 Results of the proposed method

4.3 Effectiveness of feature selection for each user

In this subsection, we investigate the effectiveness of feature selection for each user. To investigate the effectiveness, we compare the results of our method with that of the method that uses all modalities.

In this comparison, we use three metrics, false negative rate, false positive rate, and unavailable rate defined by

$$\text{False negative rate} = \frac{FN}{TP + FN + X}, \tag{8}$$

$$\text{False positive rate} = \frac{FP}{TP + FP}, \tag{9}$$

and

$$\text{Unavailable rate} = \frac{X}{TP + FN + X} \tag{10}$$

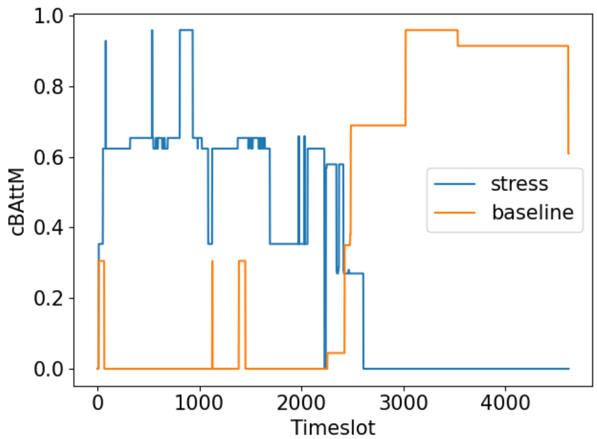
where FN, FP, TP, TN, X, and Y are the numbers of results categorized as shown in Table 6.

Table 6: valuation index

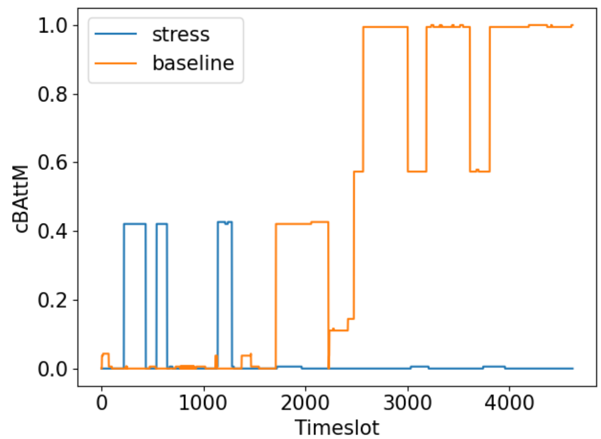
		Predicted value		
		Stress	Baseline	Confidence = 0
True value	Stress	TP	FN	X
	Baseline	FP	TN	Y

Note that all modalities are excluded for 7 subjects and only one modalities are selected for 8 subjects. In this subsection, we compare the results for remaining 22 subjects.

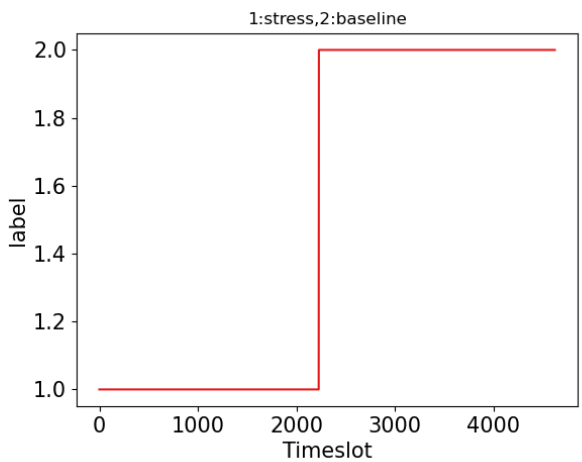
Figure 4 shows the results of integration by our method and the method using all modalities (TEMP, EDA, phasicEDA, SNMAphasicEDA, tonicEDA, BVP, HR, IBI) and all features (mean, std, min, max, range, slope) for Sub-00.



(a) Proposed method



(b) Method without feature selection



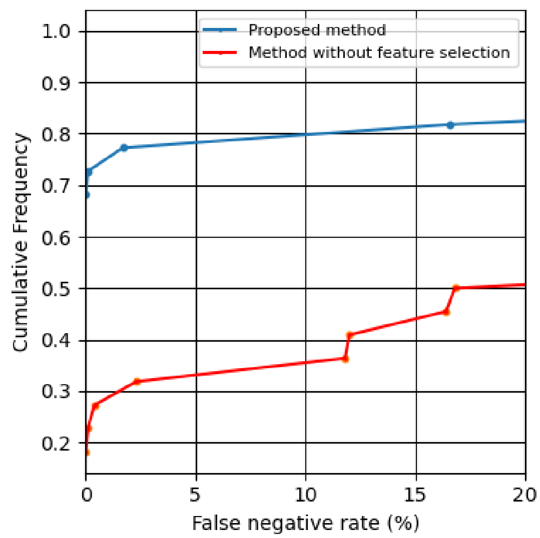
(c) Correct label

Figure 4: Sub-00 Results of proposed and comparison methods

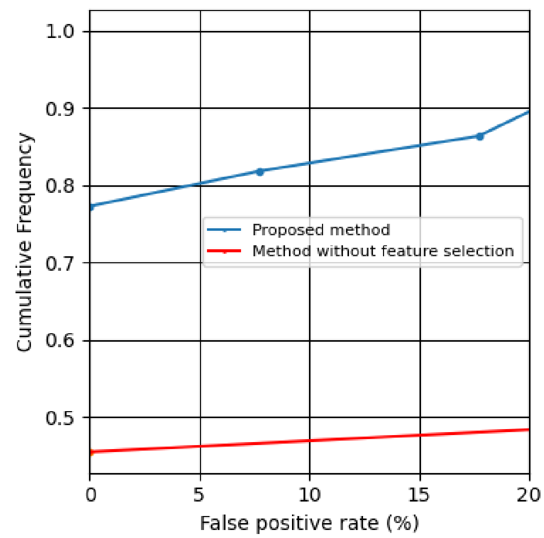
This figure shows that our method accurately detect stress while the method using all features mistakenly detect state of baseline as stress in some time slots. This is caused by the modalities that are not suitable to the subject.

Figure 5 compares the results of our method and the methods using all modalities and features. In this figure, the vertical axis is the cumulative distribution, and the horizontal axis is false negative rate, false positive rate, or unavailable rate calculated for each subject. This figure shows that our method achieves smaller false negative rate and smaller false positive rate. This is caused by selection of useful modalities for each subject. In the method without selecting modalities, some modalities that are unsuitable to the subject cause wrong decisions.

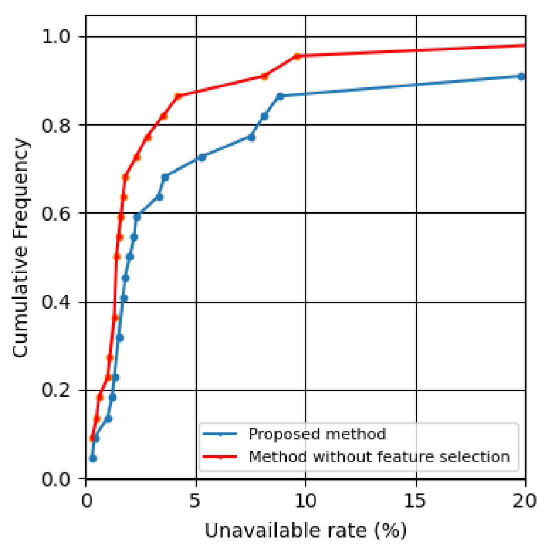
The unavailable rate of our method is slightly larger than the method without selecting modalities. This is caused by the difference in the number of used modalities. In the method using all modalities, the probability that at least one discriminator detects stress is higher than our method that uses a limited number of modalities. However, such discriminators are inaccurate. On the other hand, our method uses only the modalities suitable for each subject, and waits for the discriminators based on selected modalities to make decisions. As a result, our method detects stress accurately though the unavailable rate becomes large.



(a) False negative rate



(b) False positive rate



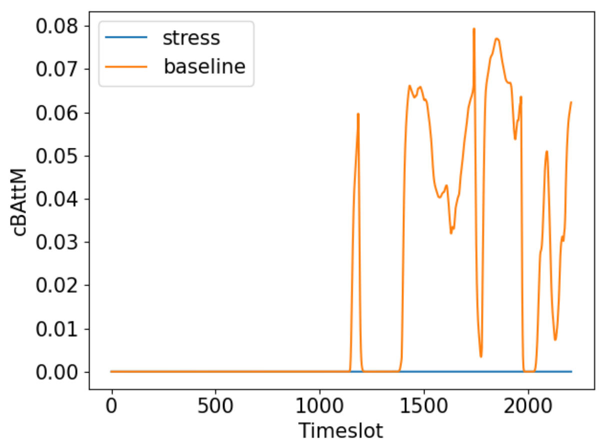
(c) Unavailable rate

Figure 5: Comparison of the proposed method with method without feature selection

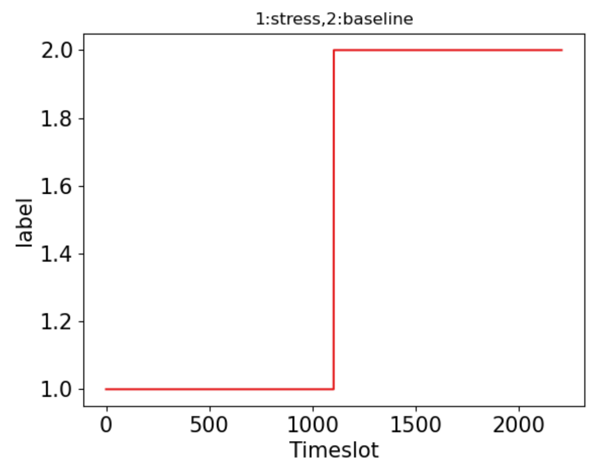
4.4 Effectiveness of exclusion of cognitive results with low confidence

Our method exclude the results of discriminator whose confidence is low. In this subsection, we investigate the effectiveness of exclusion of such results.

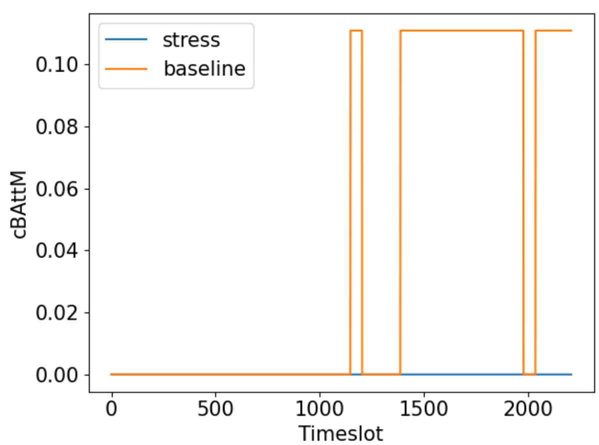
Figure 6 shows the results of the method excluding the results with confidence and the method using all results. The modality used for stress detection in Sub-02 was only TEMP. As shown in this figure, if the results with low confidence are integrated, many false positives occurs. This is caused by the results with low confidence.



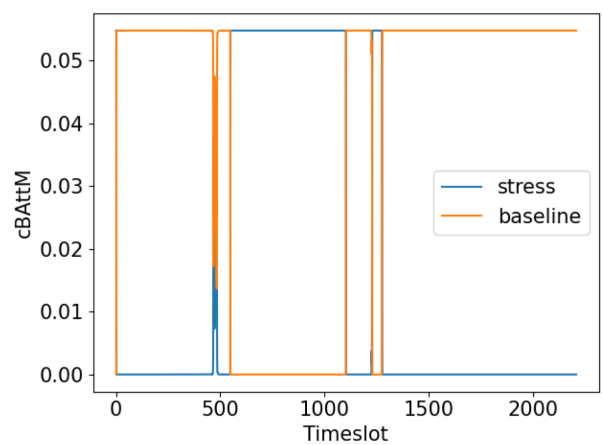
(a) Cognitive results of TEMP



(b) Correct label



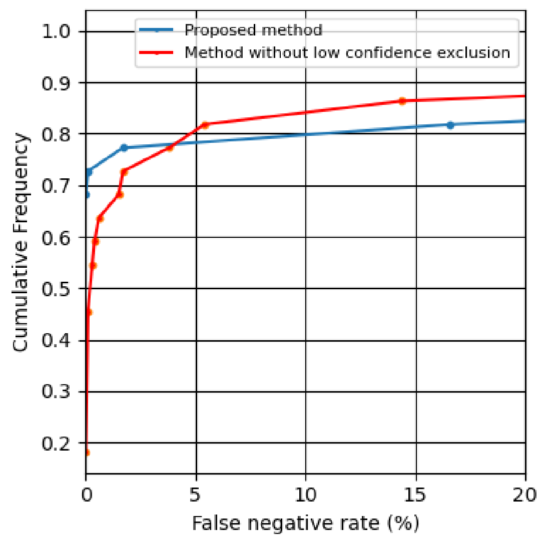
(c) Proposed method



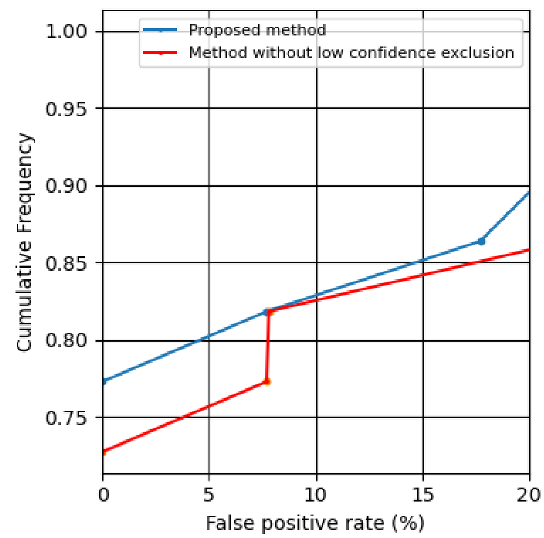
(d) Method without exclusions

Figure 6: Sub-02 Results of proposed and comparison methods

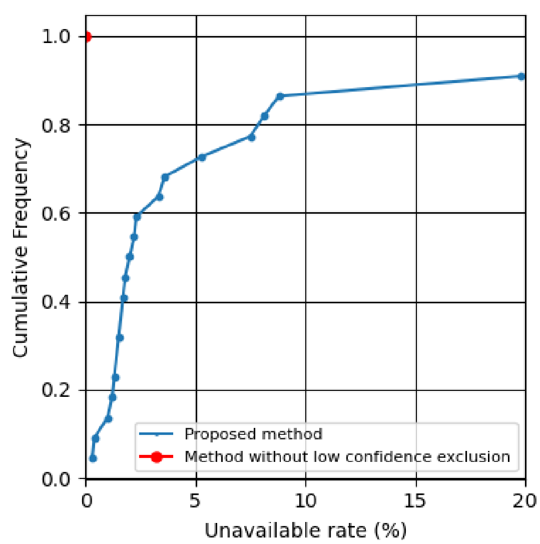
Figure 7 compares the results of our method and the methods without excluding results of discriminators with low confidence. In this figures, the vertical axis is the cumulative distribution, and the horizontal axis is false negative rate, false positive rate, or unavailable rate.



(a) False negative rate



(b) False positive rate



(c) Unavailable rate

Figure 7: Comparison of the proposed method with method without low confidence exclusion

Figure 7 shows that the unavailable rate increases by excluding the results with low confidence. This is because our method waits for discriminators to detect attacks with high confidence. But by waiting for discriminators to detect attacks with high confidence, our method achieves accurate detection as discussed above.

4.5 Future work

Our method detects stress accurately for most of subjects. However, it cannot detect stress state of some subjects, and false positive rates and false negative rates become large.

One of the reasons is the difference between subjective stress and living body response. If the living-body response is affected by the stress but the person does not feel the stress, the results of stress detection based on living-body information become different from the subjective stress.

Another reason is lack of the differences of the living-body information. If the features used in this experiment cannot distinguish the stress state, our method cannot detect stress accurately. One approach to solving this problem is to use more features so that we can select features suitable for any person. In addition, by updating the feature selection and typical values of the features, we can improve the accuracy of the detection.

5 Conclusion

In this thesis, we proposed a method to detect stress by integrating multiple types of living-body sensing information using Yuragi learning. In our method, we configure multiple discriminators based on Yuragi learning. Each discriminator makes decisions based on the corresponding information. Then by integrating the decisions of all discriminators, our method makes final decision in real time. In this method, the information used to make final decisions should be carefully selected, because the impact of stress on living-body information is different from person to person. Therefore, our methods select the information for each person and exclude the information that cannot distinguish the stress state. In addition, our method also exclude the decisions of Yuragi learning whose outputted confidence is low to avoid the detection of stress from inaccurate information.

In this thesis, we demonstrated that our method detect stress states accurately through experiments. In this experiments, we used the data obtained by subject experiments where living-body information and reports on subjective stress level were obtained. The results show that our method can detect stress accurately, while the methods without selecting modalities and without avoiding using results with low confidence cause false negatives and false positives.

However, our method could not find modalities suitable for some subjects or could not detect stress for some subjects accurately. One approach to solving this problem is to use more features so that we can select features suitable for any person. In addition, by updating the feature selection and typical values of the features, we can improve the accuracy of the detection. The improvement of the accuracy of our method is one of our future research topics. In this thesis, we set the parameters of the Yuragi learning to static values. But their suitable settings may be difference from person to person. The parameters should also be set by using the feedback from the users, which is also one of our future research topics.

Also, we demonstrated that our stress detection method can detect stress caused by room environment. However, there are other types of stress. The demonstration using the dataset of other types of stress is also one of our future research topics.

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