Estimating Emotion for Each Personality to Prevent School Dropout

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***Abstract*—This research estimates emotions of university students from their pulse waves. Negative emotion of university students causes school dropout, which is becoming a serious problem in Japan. It is indispensable for school staffs and counselors to know when and where students have negative emotion in the campus. Since pulse wave movement along with emotion changes varies with personality types, we build a model dependent on personality type, to estimate student emotion from characteristics of pulse wave movement. Experimental results show that the model for each personality type improves the accuracy of emotion estimation for new students. Positive or negative emotion estimated from pulse wave signals contributes to enhancement of campus environment by school counselors.**

***Keywords*–emotion; school dropout; pulse wave; personality**

I. INTRODUCTION

University dropout is a serious social problem in Japan. According to a survey conducted by the Ministry of Education, Culture, Sports, Science and Technology, there are the rates of student dropout were 0.42% for elementary school, 2.83% for junior high school, 1.49% for high school and 2.9% for university [1] [2].

According to Kearney & Silverman, youths are considered to drop out of school for one or more of the following reasons (functional conditions):

- To avoid school-based stimuli that provoke a general sense of negative affectivity (anxiety and depression)
- To escape aversive school-based social and/or evaluative situations
- To pursue attention from significant others
- To pursue tangible reinforcers outside of school

The first two functional conditions refer to school dropout behavior maintained by negative reinforcement, or the reduction of unpleasant physical arousal or emotional states triggered by school-based stimuli [3]. This research focuses on these functional conditions. Students who drop out of school are assumed to not be able to deal well with negative emotions and situations causing them.

M.E.Pritchard and G.S.Wilson reported the combined influence of emotional health had a significant effect on intent to drop out [4]. Therefore, the university should aware of the emotional health condition of the students so that students can maintain a positive mood.

This research estimates when and where universities students have negative emotions leading them to school dropout. The estimation of the time and places causing negative emotion enables university staff to know what kind of events in campus activities bring them negative emotion. They can provide the students with mental care, such as emotional support and introduction of counseling agency, which prevents the students from dropping out.

Emotions are estimated through periodical inspection with questionnaires, behavior observation, and measurement of physiological responses. Since frequent questionnaires are a burden to students, they are not suitable to finely grasp emotions changing over time. Settlement of equipment, such as cameras is necessary to observe behaviors. However, it records the behavior of many students, which violates their privacy. On the other hand, physiological responses can be obtained through measurement of biological data using a wearable device. Biological data correlated with emotion enables us to estimate emotions online. The combination with positioning tools, such as GPS and WIFI identifies the place where negative emotions occur.

A classifier based on machine learning is a promising means for the estimation of emotion from measured biological data. However, the transition pattern of biological data for the occurrence of specific emotion varies with individuals [5]. If we want to estimate emotions from physiological responses, it is necessary to train a classifier with the biological data brought by emotions of each student in advance for a certain period of time [6]. In a classifier trained with biological data of any student, the estimation accuracy would be significantly low, while training of a classifier with biological data of each student is a big burden for the student. We need to overcome the problem to estimate emotion from a physiological response of students.

To solve this problem, this research trains a classifier with biological data collected from students of identical personality, because transition patterns of physiological response depend on personality types [7] [8]. Students of various kinds of personalities have diversity in patterns of the physiological response to the occurrence of a specific emotion. If we train a classifier using such physiological response, we cannot expect the classifier to extract the common patterns of physiological response. In this research, the emotion is estimated using classifiers trained with the physiological response of students similar in their personality type. Since a classifier is prepared for each personality type, the emotion of a new student can be estimated only with the student answering a quick personality

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test.

In this research, experimental results show classifiers for each personality type improved the accuracy of emotion estimation for new users. For each personality type, there was a difference in estimation accuracy, the pattern of the physiological response, and important variables. Among elements composing personality, the extroversion and the neuroticism seem to play a vital effect on the estimation accuracy. People strongly extroverted are likely to have positive emotion, while those who have high neuroticism are likely to be sensitive to stimulation. It is inferred that there was a difference in biological data and variables of importance because neuroticism certainly affects heart rate and Low-Frequency (LF) component/High-Frequency (HF) component of heart rate variablity, while extroversion, openness, and agreeableness certainly affect the natural log of LF.

A classifier for each personality type would tell the time and place for which university students have negative emotion in an on-line manner. For students who have negative emotions, such as anger and sorrow, it would be possible to provide support, such as keeping an eye on them, giving them a phone call, and introducing them to a counseling agency.

The rest of the paper is structured as follows. In Section 2, we show existing research about determinate emotions. In Section 3, we show the use case and method of my study. In Section 4, we show the experimental result. In section 5, we discuss from experimental result. Finally, we conclude in Section 6.

II. Existing Research

Section II describes the advantages and disadvantages of existing methods to determin emotions. A scale is necessary to determine emotions. The scale includes psychological scales to examine subjective emotional experiences, behavior scales based on external reactions, and biological scales based on internal responses.

The psychological scale includes the introspective method, the Likert scale, the rating scale method, the open-ended question method, the questionnaire method, and so on. Since these scale methods require students to answer big questionnaires, they have difficulties to obtain data of many university students.

The behavior scale needs permanent acquisition of various nonverbal behaviors, such as facial expression, posture, attitude, gesture, and voice. Although behavior data can be obtained through a lot of measuring equipment in many places, it causes privacy violation.

The biological scale uses both of autonomous reaction by activities of the autonomic nervous system and voluntary reactions by activities of the central nervous system. The former includes blood pressure, heart rate, skin electrical reflection, skin temperature, and blood flow rate, while the latter includes brain waves, electromyograms, and respiration. The wearable device for determination equipment enables to obtain those biological data all the time. Emotions can be estimated in an online manner from them.

However, physiological responses when each emotion occurs often do not match. The reason is that the physiological response patterns are different among individuals [5]. Leon has optimized classifiers with training using biological data for each person to eliminate individual differences in physiological response [6]. Since personalized classification method requires time for the training using individual biological data, new users cannot use it immediately.

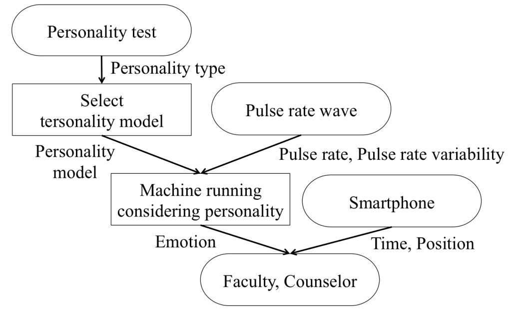

Figure 1. Estimating emotions considering personality

In order to obtain a practical solution to know the timing when each university student has a negative emotion, we need a method many users can use easily on the spot. These existing methods are not suitable for easy classification of student emotions.

III. Emotion Estimation with Personality

A. Use Case

This sections describes the method to estimate emotions in this research. Emotions are estimated from biological data considering personality. Students take a personality test to select a classifier according to their test result. The method estimates emotions from heart rate and its variability using a wearable pulse wave meter. Various wearable devices have been developed and operated in the field of health care and sports in recent years [9]. For students wearing a pulse wave meter, an application on a smartphone estimates negative emotions. Once it finds a student who often suffers from negative emotion, it notifies faculty and counselors of the information, to provide the mental care for the student. Figure 1 shows an operational diagram of the method.

B. Estimating Personality

In this section, a personality and the method to estimate personality are described. There are typology theory and property theory in the ways of grasping a personality. The typology theory applies a personality to a stereotype set based on psychological or biological characteristics. The typology theory is intuitively easy to understand, but the intermediate type is likely to be ignored in the theory. It is also difficult for one type to move to another. On the contrary, in the characteristic theory, the personality is composed of several characteristics. It expresses personality with multi-dimensions for quantitative comparison. The characteristic theory has the disadvantage that it is difficult to grasp the identity of personality. However, we can analyze personality statistically. It is also possible to grasp the personality in a typological way, if we classify subjects from a certain viewpoint.

The characteristic theory is used in this research. The Big Five test expressing personality with five factors is considered to be the most influential test in the characteristic theory. The five factors are neuroticism, extraversion, openness, agreeableness, and conscientiousness [10]. Neuroticism responds sensitively to external stimuli and shows emotional instability trend. Extroversion indicates a tendency to actively appeal to the outside world. People with high extroversion tend to have

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positive emotions. It means openness to experience. It shows a rich tendency for thought and images. Agreeableness shows a tendency to synchronize with other people in relationship with people. Conscientiousness shows a tendency to overcome things with clear purpose and intention.Conscientiousness is a dimension related to control of impulses.

Emotion is presumed to be affected by neuroticism related to anxiety causing emotional instability. It is also likely to be affected by extraversion leading to positive emotions.

C. *Classifiers Based on Heart Rate*

The students use the wearable device to measure biological data.We measure the heart rate and the heart rate variability. This section describes heart rate. The heart rate increases with anger, fear, and sadness, not with joy, surprise, and disgust [11]. The activity of the human autonomic nervous system changes when the emotion changes. The activity of the autonomic nervous system is measured from the frequency response of heart rate variability [12]. From the heart rate variability, the following components can be obtained; Very Low-Frequency (VLF) component (frequency is 0.0033 to 0.04 Hz), Low-Frequency (LF) component (frequency is 0.04 to 0.15 Hz), High-Frequency (HF) component (frequency is 0.15 to 0.5 Hz), Total Power (TP) component (the sum of the three frequency components), Standard Deviation (SD) of pulse record (PR) interval, RMssd (whose the deviation of the difference between adjacent PR intervals)

The value of HF indicates the enhancement of parasympathetic nervous system, while the value of LF/HF indicates the sympathetic nerve system. TP indicates the activity degree of autonomic nervous system. RMssd indicates the tension degree of the vagus nerve. This research uses a pulse wave meter attached to the earlobe.

D. *Create Personality Model*

This section describes how to classify personality. The estimation system in this research uses TIPI-J invented by Japanese as a scale of Big Five [13]. Since TIPI-J is a simple scale that can measure five personality traits with each of two items, the burden on students is small. The estimation system figures out personality vector on the basis of the five personality traits with TIPI-J. After it classifies them, it calculates the centroid vector of each cluster by the k-means method [14], to create a personality model. A new student is classified into the nearest cluster based on the distance from the personality vector of the student to the centroid vector of the cluster. The number of personality clusters is determined to the most appropriate one, trying from 2 to 6 clusters in the experiment.

E. *Emotion Estimation along Personality Model*

Supervised machine learning creates emotional classifiers. The emotional classifier is created for each personality model. The explanatory variable of the emotional classifier is heart rate and heart rate variability, while the objective variable specifies whether the student has negative or positive emotion.

To know the student has negative or positive emotion, we use the Circumplex Model and the Affect Grid proposed by Russell [15] [16].The Circumplex Model expresses all emotions in two dimensions of the pleasant-unpleasant one and the arousal-sleepiness one.The Affect Grid is an evaluation method of emotions, based on a Circumplex Model. It is formed in a square grid composed of 81 squares of 9×9.

It is considered that the accuracy to estimate emotion improves, if the biological data is classified into groups having common patterns. The personality is used as the scale for the classification. Section 3.2 shows that personality traits affect brain functions and body reactions. Some research reports that there is a difference in the balance of autonomic nervousness depending on personality [7] [8]. It is expected that common patterns of biological data can be extracted if students are classified according to personality models. The classifier for each personality model of the user would estimate the emotion more accurately than one ignoring the difference in personality.

IV. RECALLING EXPERIMENT

A. *Purpose and Method of Experiment*

This section describes the experiment conducted in this research. Experimental results show that the personality model improves the accuracy of emotion estimation. Our subjects are 20 university students, 10 male and 10 female. Heart rate and heart rate variation were calculated from pulse wave signals obtained by a wireless earlobe pulse wave device, Vital Meter made by TAOS Institute [17].

Three types of emotions obtained through experiments were positive emotions, negative emotions, and emotion during relaxation. After the subject recalled one of pleasure events, anger events, and the others, we estimated their emotion. The recall time was 2 minutes. We conducted each of three types of emotion estimation after recalls five times.

We used the random forest to create classifiers. Explanatory variables are 17 variables in total. They include the average, the minimum, and the maximum of heart rate, beat count (heart rate at all measurement time), SDNN, RMssd, and the average of VLF, LF, HF, LF/HF and TP. It also includes the standard deviation of heart rate, VLF, LF, HF, LF/HF, and TP.

The objective variables are two variables; one means the student has positive emotion, while the other means negative emotion. To obtain the objective variable, the subject's emotion was attained with the Affect Grid. In the pleasant-unpleasant dimension of the Affect Grid, the center was set to 0. We regarded +1 to +4 as positive emotion, while -4 to 0 as negative emotion.

To show that the personality model works effectively, the classifier created from 20 subjects without classification by personality model was compared with the classifier trained for each personality model.

In the former, data of 20 subjects was divided into twenty pieces, one for each subject, and the 20-part cross-validation was carried out. In the latter, a classifier was created for each personality model resulting from clustering of the five personality traits of 20 subjects with the k-means method. After the data was divided into the number of subjects for each personality model, the cross validation for the number of subjects was carried out for each personality model.

B. *Estimation Accuracy by Personality Model*

We compared the estimation accuracy by the cross-validation of classifiers that do not classify personality models as well as classifiers for each of two to six personality models. The f-measure, a harmonic mean of the precision and the recall was used as an evaluation index of the estimation accuracy. When the personality is not classified, the F value is 0.501.

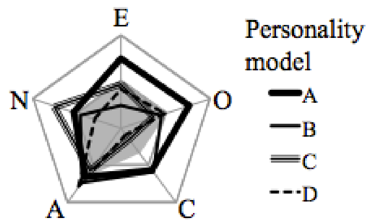

Figure 2. Personality Traits of Each Personality Model

TABLE I. P-VALUE ON EACH PERSONALITY MODEL

Compared	E	O	C	A	N
A:B	0.032	0.345	0.947	0.776	0.861
A:C	0.100	0.018	0.015	0.713	0.154
A:D	0.084	0.209	0.058	0.460	0.199
B:C	0.245	0.879	0.065	0.491	0.079
B:D	0.367	0.998	0.140	0.935	0.448
C:D	0.999	0.793	0.927	0.220	0.097

The best of estimation accuracy is 0.557 when the personality model is classified into four.

Figure 2 shows the codebook of each personality model when the personality model is classified into four. In the score of 5 personality traits by TIPI-J, the minimum is 2, while the maximum is 14. The gray marker shows the average values of all 20 subjects. Personality model A, B, C, and D involved 8, 5, 4, and 3 subjects, respectively. From Figure 2, personality model A is sociable, strong in outstanding curiosity and self-control, because of the high extraversion, openness, and conscientiousness. Personality model B is introverted, strong in intention and diligence, because of the low extraversion and high conscientiousness. Personality model C believes to be sensitive to the stimulus, has a solid idea, is unique, and accepts himself/herself as he/she is, because of the high neuroticism and low openness, agreeableness, and conscientiousness. Personality model D understands the psychological state of the others, is insensitive to stimulation, and has high impulsivity, because of high agreeableness, low neuroticism and conscientiousness.

We applied the Steel-Dwass test, which is a multiple comparison test [18], assuming that the score of personality traits of each character model can be described as ”there is no difference between the average values of both groups”. Table I shows the obtained p-value as a result of the Steel-Dwass test. The row of ”A: B” in the column of ”Compared” in Table I shows the result of comparing personality traits of personality model A and personality model B. The rejection region of p-value was set to 0.1. As a result, the personality models A and B showed the significant difference in extroversion, A and C showed it in openness and conscientiousness, A and D showed it in extraversion and conscientiousness, B and C showed it in conscientiousness and neuroticism, C and D showed it in neuroticism.

Next, Figures 3 to 5 show the comparison of the average values and dispersion of f-measures in each personality model when classified and not classified with the personality model. ”Non” is the average value of the f-measure of persons belonging to each personality model when 20-part crossing verification was carried out without considering personality. ”CP” is an abbreviation considering personality, which is the average of f-measure when cross-validation is carried out only

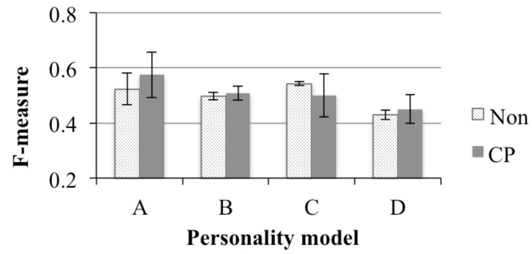

Figure 3. F-measures of Positive Emotion

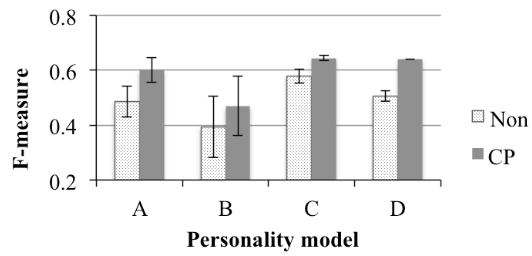

Figure 4. F-measures of Measures of Negative Emotion

for persons of each personality model when personality is considered.

The f-measure of positive emotion in personality model C decreased when personality was considered, but f-measure in the other personality model increased. Personality model C with high neuroticism had the greatest CP of negative emotion among other personality models, and D of low neuroticism is the greatest Non-CP of negative emotion. Moreover, personality model A with high extraversion had the greatest CP and Non-CP of positive emotion. Although dispersion of negative emotion decreased in all personality models, the dispersion of positive emotion, the average of dispersion of positive and negative emotion rose.

C. Emotions for Each Personality Model

Figure 6 shows a graph of biological data for each personality model. The Steel-Dwass test is applied assuming that there is no difference between the average values of both groups regarding biological data of each personality model. If the rejection area of the p-value is 0.1, a significant difference was observed in the average value and standard deviation of LF/HF of personality models A and D.

Table II shows the values of the questionnaire after recalling. The value is represented by the effect grid. Table II shows the range of positive emotion and negative emotion on the pleasant axis and the arousal axis for each personality model. On the pleasant axis, 1 to 4 corresponds to the positive emotion, while -4 to 0 to the negative emotion. Both of the emotions become stronger as the absolute value increases. Moreover, the range on the arousal axis is -4 to 4 for any emotion. As shown in Table II, personality model C seems to have a low arousal level. However, p-value with multiple comparison tests for the questionnaire after recalling presented no significant difference, if the rejection area is set to 0.1.

Table III shows the top 5 of the variable importance in each personality model in the random forest. It turned out that the importance of the explanatory variables is different depending on each personality model. In the comparison of personality model A with personality model D, A has at least 2.9, whereas D is less than 1 for every variable.

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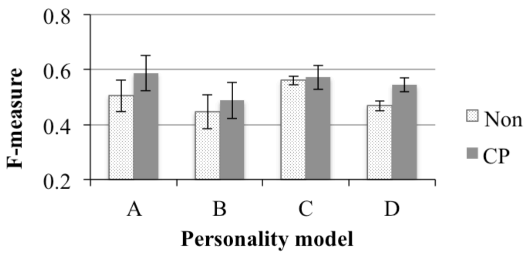

Figure 5. F-measures of Positive and Negative Emotion

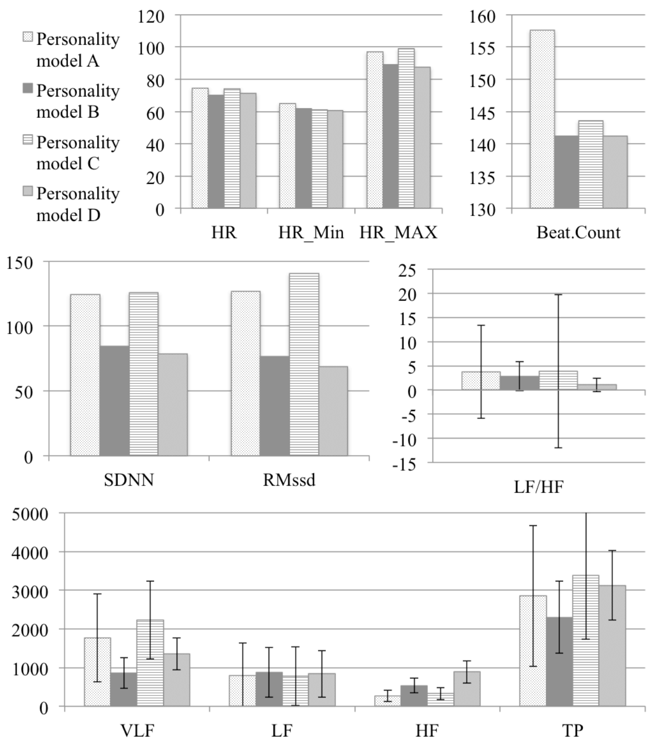

Figure 6. Biological Data of Each Personality Model

V. Discussion

A. Personality and Estimation Accuracy

For each personality model, we investigate the estimation accuracy of the classifiers incorporating the personality models and the classifier neglecting the personality models. Let us denote the estimation accuracy of the former with CP, while that of the latter with Non. The increasing rate of the difference of CP from Non for personality model A is the largest, 0.082, compared with other personality models. Personality model A is the highest in the extraversion. Those who are highly extroverted are said to feel positive emotions, which seem to increase the accuracy of positive emotion. Personality model B has low value both in Non and CP.

The activity of autonomic nerves was mild in personality model B, because the value of TP indicating the degree of activity of autonomic nerves was low. Personality model B is considered to be unlikely to change biological data because of its low extraversion as well as introverted and calm personality. In personality model C, CP of positive emotion decreased, while CP of negative emotion was 0.644, which was the largest

TABLE II. RANGES ON PLEASANT AND AROUSAL AXES

Emotion	Personality Model A Positive	Personality Model A Negative	Personality Model B Positive	Personality Model B Negative
pleasant axis	2.352	-1.439	1.786	-1.281
arousal axis	0.407	0.227	-0.179	-0.031

Emotion	Personality Model C Positive	Personality Model C Negative	Personality Model D Positive	Personality Model D Negative
pleasant axis	2.333	-1.167	1.696	-1.591
arousal axis	-0.667	-0.833	0.565	-0.273

TABLE III. TOP 5 VARIABLE IMPORTANCE

Rank	Personality Model A		Personality Model B	
1st	LF_AVG	5.002	VLF_AVG	1.820
2nd	HR_AVG	4.282	HF_SD	1.594
3rd	HR_Min	3.892	RMssd	1.341
4th	LF/HF_AVG	2.985	VLF_SD	1.330
5th	LF_SD	2.949	LF/HF_AVG	1.274

Rank	Personality Model C		Personality Model D	
1st	HF_AVG	2.604	LF_SD	0.908
2nd	HF_SD	2.310	SDNN	0.713
3rd	LF_AVG	2.205	RMssd	0.711
4th	HR_Min	1.958	LF/HF_AVG	0.650
5th	TP_AVG	1.542	LF_AVG	0.633

among all personality models. Since it has high TP, autonomic nervous activities are assumed to be intense in personality model C. Personality model C is sensitive to stimulation and feels anxiety because of its high neuroticism, which seems to affect the estimation accuracy of negative emotion. Since personality model D is introverted and has a low neuroticism, it is considered that its emotion is calm and stable. It is thought that the estimation accuracy of positive emotion was low. People with high agreeableness are reported to have high-stress values [19]. The estimation accuracy of negative emotion was good because of stress accumulation.

As a countermeasure to the personality model with low estimation accuracy, we can add behavior data, such as GPS logs and acceleration to explanatory variables. Since changes in biological data are unlikely to occur in low-accuracy models, it is considered that the accuracy can be improved with behavior data.

B. Influence of Personality and Biological Data

As a result of multiple comparisons of each biological data for each personality model, a significant difference was found in the average value and standard deviation of LF / HF of personality model A and personality model D. There was no significant difference in the questionnaire after a recall by each personality model. However, there was a significant difference in extraversion and conscientiousness in the personality traits of personality model A and personality model D. From the above, it is considered that extraversion and conscientiousness have influenced the average value and standard deviation of LF / HF with respect to personality model A and personality model D. Eysenck states that extroverts have a high level of restraint of the cerebral cortex caused by the reticular activating system, while introverts have a high arousal level [8]. Extroverts are insensitive to stimulation. Their cerebral cortex awakening is late, or the awakening falls quickly even if it gets awaken. On the other hand, introverts are sensitive to stimuli. Their cerebral cortex tends to awaken excessively even with a small stimulus. Therefore, the extrovert type is considered to have low physiological excitement. Buck, Miller&Caul [20] also showed that an extrovert person has a weak autonomic nervous system reaction. From the above, it is expected that the value of LF/HF will be low in personality model A who is high in the extraversion and insensitive to stimulation. On the contrary, the value of LF/HF would be high because personality model D is low in the extraversion and sensitive to simulation. However, the result was different. Personality model A with high extraversion had a high LF/HF value, while personality model D with low extraversion had a low LF/HF value. Although this research evaluates the extraversion as five factors in the Big Five, Eysenck evaluates it in the extrovert - introvert dimension. Because of it, the difference seems to have occurred.

The extrovert described by Eysenck has traits, such as sociability and impulsivity. On the other hand, extraversion by the Big Five is considered to be cautious with identifying it as sociability. In the Big Five, shyness is not extraversion. It considers the shyness corresponds to high anxiety and neuroticism in almost all cases [10]. In addition, the impulsivity of Eysenck's extrovert can be seen as conscientiousness of the Big Five. Therefore, although personality model A has high extraversion, it has high conscientiousness and low impulsivity. It is presumed to be different from extrovert described by Eysenck. The expectation that the value of LF/HF will be high is not adapted because personality model D with low extraversion is sensitive to stimulation.

Eysenck also states that people with high neuroticism are more likely to arouse the autonomic nervous system while people with low neuroticism are less likely to be aroused. Therefore, it seems that the value of the standard deviation of LF/HF was low because of the low neuroticism in personality model D.

Regarding the fact that explanatory variables emphasized in each personality model shown in Table III are different, it is presumed that biological data affected by personality are different. Kobayashi showed that the natural log of LF is correlated with openness and agreeableness during rest, while extraversion during calculation [21]. It is considered that the average value of LF is a variable of high importance for personality model A with high outgoingness and openness, while the standard deviation of LF is the variable of the highest importance for personality model D with agreeableness. Besides, Nagamine and Nakamura [22] show that there is a positive correlation between neuroticism and the degree of stress. They also state the degree of stress and the heart rate have a positive correlation. In the personality model C with a high neuroticism, it coincides with the fact that the average value and the maximum value of the heart rate are large, and the minimum value of the heart rate is the variable of the top importance.

VI. CONCLUSION

This paper addressed the school dropout problem of university students. As a method of estimating negative emotion, the paper proposed a method to estimate emotions considering personality.

From the experimental results, it was found that the estimation accuracy improves, if the classifier is trained for each personality model. Personality traits of each personality model were suggested to be related to biological data and variable importance. From the above, individual differences in physiological response differ from each personality type.

As future work, it is necessary to look at the correlation to see how the personality traits exactly affect biological data. The incorporation of gender difference could be one way to improve the accuracy. Linking time and location information to the estimated emotions, faculties and staffs can prevent school dropout of students with mental care, such as emotional support at a good timing.

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