Daily Health Condition Estimation Using a Smart Toothbrush with Halitosis Sensor

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Abstract. The number of occupational injury claims and certifications for mental disorders increases every year. Therefore, the Ministry of Health, Labour and Welfare of Japan (MHLW) has mandated annual stress checks as a countermeasure. This gives rise to the having a daily health measurement using IoT devices. However, it has been found that managing multiple devices and active measurement behavior decreases users' motivation. This paper proposes a health measurement system that can be integrated with traditional brushing tools enabling a smooth gauging of health measures. This is done while people are performing their daily teeth brushing activity without any extra overhead. The proposed method estimates the recovery index for fatigue based on halitosis collecting by a smart toothbrush with a halitosis sensor. To evaluate the proposed method, we collected halitosis data and questionnaires about recovery index from 12 subjects every day for approximately two months and constructed a model to estimate each item of the questionnaires by Random Forest based on the halitosis data. As a result, we found a significant difference between the halitosis data and two measures of the recovery experience (MA and PD); furthermore, we achieved MA with an f-score of 0.60, PD with an F-score of 0.58 for three value classification, and sleep quality with an F-score of 0.71 with binary classification.

Keywords: Recovery estimation · Smart toothbrush · Measurement system

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1 Introduction

The Ministry of Health, Labor and Welfare (MHLW) of Japan reports that the number of workers' compensation claims and certifications for mental disorders has been increasing every year in Japan [18]. In particular, the number of claims has increased tenfold in the past 20 years [16]. For a countermeasure, MHLW has obligated companies to offer annual stress checks [17] to employees in Japan. However, they can not observe minute changes in the mental status of workers and respond to mental health problems at the appropriate timing by the annual stress checks due to low frequency. For this reason, periodic and long-term observations are essential for keeping mental health and improving work performance.

On the other hand, IoT devices for measuring health conditions have become popular in recent years. These IoT devices can collect sensor data such as heart rate and sleep quality to measure health from various perspectives. However, if a user actively uses multiple IoT devices, he/she must understand how to use each device and manage applications for each device. In the use of multiple wearable devices, the users must periodically recharge each devices respectively. These periodically troublesome procedures reduce the motivation of users to continue health measurements; therefore, a way to continue using IoT devices in the long term is necessary [19].

This study proposes a system that estimates fatigue recovery while the user keeps motivation for health measurement in the long term. Recovery refers to the process of recovering from a stressed state [22]. It has been suggested that the process of recovery from work stress may be related to individual health and well-being and work performance [5]. Therefore, regular and long-term checks focusing on recovery are important for work. To keep the user's motivation for health measurement, we melt health measurement into the tooth brushing behavior that most people perform daily. Many people perform tooth brushing at waking up when the result of fatigue recovery appears prominently. Especially, halitosis is known as the link between stress [11]; therefore, we assume that the morning halitosis changes depending on the stress and recovery experience in the previous day. Therefore, the proposed system collects the halitosis data by a smart toothbrush with a gas sensor before the morning tooth brushing and then estimates the recovery based on the data. In the procedure, the users breathe to a toothbrush to measure recovery; there is no trouble for measurement.

We build a model that estimates recovery from halitosis data collected in tooth brushing. The estimation model is constructed by the Random-Forest algorithm with the halitosis data consisting of odor, temperature, humidity, pressure as input data and outputs the estimation of recovery index.

To evaluate the proposed method, we collected halitosis data and questionnaires about recovery index from 12 subjects every day for approximately two months and constructed a model to estimate each item of the questionnaires by Random Forest based on the halitosis data. In the experiment, each subject used a smart toothbrush (SMASH) with a gas sensor and collected halitosis data before brushing in the morning. In addition, as the ground truth of the training model, each subject answered the questionnaire about recovery used in research on industrial insurance [2,6,21,22] in/after tooth brushing.

As a result, we found a significant difference in halitosis data among three degrees about the two measures of recovery experience (Mastery and Psychological detachment). Furthermore, we achieved Mastery with an f-score of 0.60, Psychological detachment with an F-score of 0.58 for three value classification, and sleep quality with an F-score of 0.71 with binary classification.

The contributions of this study is that We have realized less burdensome recovery measurement by incorporating sensing into daily tooth brushing behavior.

2 Related Works

2.1 Health Status Measurement Using IoT Devices

In recent years, a variety of health monitoring systems using IoT devices have been proposed [15]. Zhang et al. [23] develop a necklace-type IoT device monitoring human eating habits such as the number of feeding to detect eating disorders and real-time intervention. Leng et al. [13] propose a drowsiness detection system using a wristband type device. When the driver wears this device, it acquires sensor data and extracts features such as heart rate, pulse fluctuation, and respiratory rate based on the sensor data to detect drowsiness. Bui et al. [4] analyze whether it is possible to intervene in diabetic patients from IoT devices. Proposals for lifestyle improvement from IoT devices improve glycemic control by 0.8% on average in one year compared to conventional care for patients with type 2 diabetes. Inan et al. [8] provide remote monitoring of heart failure patients using wearable devices. By evaluating whether or not hospitalization is necessary for patients with heart failure using the lifelog of cardiac function collected from wearable terminals, it is possible to adjust the treatment specific to the patient and reduce the number of hospitalized patients.

Thus, using IoT devices, including wearable terminals, enables users to measure their health over a long period. However, more frequent management of IoT devices and more actions required for health measurements can have a negative impact on users.

Bonai [19] examines the possibility of diabetes treatment using IoT, and it is expected that long-term utilization of IoT affects improving blood glucose. However, without support, the IoT utilization rate will be low, more than 10% stop using it immediately after the introduction of IoT (within 2 weeks), and it is difficult to maintain motivation in about a year.

2.2 Relationship Between Oral Condition and Health

There are studies aimed at monitoring oral conditions. Shetty et al. [20] have developed a Remote Oral Behaviors Assessment System (ROBAS) using an electric toothbrush and a smartphone. It shows the possibility of accurately and reliably monitoring the brushing pattern in the home for a long time. Islam et al.

[10] have proposed a system for monitoring pH in the oral cavity. They mention the system can monitor a decrease in PH, an indicator of bacterial accumulation in the oral cavity, using a piezoelectric dental crown, while compensating for lost teeth.

On the other hands, Various studies were conducted on the relationship between oral condition and the psychological condition and quality of life.

A study investigating the relationship between depression, stress, self-esteem, and the short-form oral health impact profile (OHIP-14) in middle-aged women has reported that the lower the stress and the higher the self-esteem, the higher the oral health impact index [12]. A study of 452 university students investigating the relationship between stress and oral symptoms using a self-reported questionnaire has reported that stress has a profound effect on the symptoms of dry mouth, bad breath, and temporomandibular joint pain [14].

A study also investigates the relationship between oral health and general health and quality of life in elderly male cancer patients [9]. It concludes elderly male cancer patients who have problems with their mouth and teeth and have difficulty eating may have a lower quality of life, poorer mental health, and lower levels of physical function than those without these problems.

Based on these, it can be seen that the relationship between oral condition and stress is mentioned in a wide range of age groups. Understanding the oral condition is also important for improving one's mental and quality of life. In this study, we think that the relationship between bad breath and health conditions also occurs for recovery.

2.3 Positioning of This Study

Maintaining user motivation is an issue for continuous monitoring with IoT devices. Therefore, to eliminate the disadvantages of using IoT devices, we propose a health measurement method that is less burdensome for users in this study. By focusing on tooth brushing, users don't have to do new actions only for measuring health.

3 Smart Toothbrush System

3.1 System Overview

In this study, we propose a system that collects halitosis and estimates recovery by the flow of tooth brushing that many people perform every morning. Normally, a dedicated device is required to collect halitosis, but in proposed method, We use a smart toothbrush that integrates brushing teeth and collecting halitosis. Since toothbrushes are indispensable in daily life, users can reduce the trouble of managing and charging new equipment. All users have to do to collect halitosis is to press the button on the toothbrush and blow for 3-5 s. using halitosis collected from a smart toothbrush, users' recovery is estimated. It is known that there is a correlation between halitosis and poor lifestyle and stress [11], and we think that there is also a correlation between recovery and halitosis.

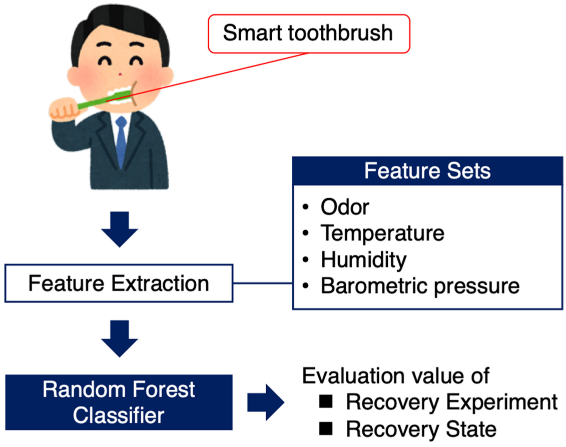


Fig. 1. overview of the recovery estimation model

3.2 Recovery Estimation Model

We describe the model that estimates recovery from collected halitosis data. The Fig. 1 shows the outline of the recovery estimation model.

Four types of features, odor, temperature, humidity, and barometric pressure, are extracted from the breath blown by the user. For temperature, humidity, and barometric pressure, extract their median values during a single measurement.

The output of this model is the evaluation value of recovery. In this study, the evaluation values are treated in two or three stages for each recovery measure. Therefore, a 3-class or 2-class classifier is used for each recovery measure. Random-Forest Classifier is used as the model for classifying recovery evaluation values. That is because we thought that it could be classified by clear numerical conditions according to each feature of halitosis. For the ground truth, we use the recovery questionnaire used in industrial insurance.

4 Questionnaire About Recovery

In this chapter, we describe the questionnaire used in the experiment. Recovery refers to the process of recovering from a stressed state [22]. It has been suggested that the process of recovery from work stress may be related to individual health and well-being and work performance [5]. There are two indicators for recovery: (1) recovery experience and (2) recovery state. Below, we explain the two indicators and describe the creation of the questionnaire based on them.

4.1 Recovery Experience

Recovery experience is an index of experience of recovering from stress such as work. Although the behavior for recovery varies from person to person, the underlying experience is divided into four distinct measures by Sonnentag et al. [22]. The four measures are Psychological detachment, Relaxation, Mastery, and Control. We describe these measures based on Sonnentag et al. [22].

Table 1. Recovery experience questionnaire

Q-1	I feel like I can decide for myself what to do	CO
Q-2	I learn new things	MA
Q-3	I forget about work	PD
Q-4	I decide my own schedule	CO
Q-5	I don't think about work at all	PD
Q-6	I kick back and relax	RE
Q-7	I seek out intellectual challenges	MA
Q-8	I do things that challenge me	MA
Q-9	I determine for myself how I will spend my time	CO
Q-10	I distance myself from my work	PD
Q-11	I do relaxing things	RE
Q-12	I use the time to relax	RE
Q-13	I take care of things the way that I want them done	CO
Q-14	I take time for leisure	PD
Q-15	I do something to broaden my horizons	MA
Q-16	I get a break from the demands of work	RE

PD = Psychological detachment, RE = Relaxation, MA = Mastery, CO = Control

Table 2. Recovery state questionnaire

Q-17	This morning I was able to physically refresh
Q-18	This morning, I was able to mentally refresh
Q-19	How do you rate your sleep quality as a whole?

Psychological detachment means not in a physical sense, such as leaving the workplace but keeping a distance from work in a psychological sense. You can recover from the effects of work stress by keeping a distance from work in a psychological sense. It is also known that psychological detachment affects the relationship between stress factors and the prevention of burnout [7].

Relaxation is a process related to leisure activities. It has been suggested that working for a long time in stressful work leads to illness caused by the work stress factors [3]. Therefore, relaxation is important to prevent such a situation. It is also known that the positive emotions obtained from the experience of relaxing play a role in reducing the influence of negative emotions [22].

Mastery refers to non-work activities other than work by providing rewarding experiences and learning opportunities outside of work. These activities are expected to affect recovery because it leads to the acquisition of new skills and qualifications and improving self-efficacy [1].

Control is the ability of a person to choose an action from two or more options. Here, it refers to the extent to which a person can decide what kind of activity he/she will perform in his or her leisure time and when and how he/she will perform the activity. This experience suggests that increasing feelings of self-efficacy and ability promotes well-being and enhances recovery.

In the questionnaire used in this study, we asked about how to spend time after the day's work to check the recovery experience of the subjects. We prepared a total of 16 questions, 4 for each of these 4 measures. The questions are shown in Table 1 and are quoted from reference [21,22]. All questions are rated on a scale of 5 from "1. Not applicable at all" to "5. Very well-applicable".

4.2 Recovery State

Recovery state refers to the state after recovery during the leisure period. There is a correlation between morning recovery and work performance for the day [2]. Therefore, checking the recovery status in the morning is important for workers to face their work.

In this study, we created a questionnaire quoting the mental and physical refreshment used in Reference [2] and the questions about sleep quality from Reference [6]. Reference [6] is widely used as an evaluation of sleep disorders.

Table 2 shows the actual questions and their order. There are two questions about refreshing mentally and physically: "This morning I was able to physically refresh" and "This morning, I was able to mentally refresh". These questions are rated on a scale of 5 from "1. Not applicable at all" to "5. Very well-applicable". The question about sleep quality is "How do you rate your sleep quality as a whole?". This question is rated on a four-point scale from "1. very bad" to "4. very good".

5 Experiment

In this section, we describe an experiment to evaluate a recovery estimation model based on halitosis data. The purpose of this experiment is to verify whether the recovery experience and recovery state can be estimated from the halitosis data when waking up. The period is two and a half months, and the number of subjects is 12. In the following sections, we describe the data collection, the evaluation method of the collected data, and the evaluation results.

5.1 Data Collection

In this section, we describe how to collect data for recovery estimation. To collect halitosis data, we used a smart toothbrush "SMASH" developed by NOVENINE Co., Ltd.[1], that can measure halitosis by a gas sensor (Fig. 2). The subjects blew on the smart toothbrush to measure halitosis data before tooth brushing in the morning. The subjects collected their halitosis data using SMASH as soon as getting up every morning. All the subjects have to do for measuring is press the button on SMASH and blow for about 5 s before tooth brushing. In addition, they answered the questionnaires shown in Sect. 4 by smartphone in/after tooth brushing. In the experiment period of approximately two and a half months, we collected valid data of 581 days.

Fig. 2. A smart toothbrush "SMASH" developed by NOVENINE Co., Ltd.

5.2 Analysis of Collected Data

We verified whether the recovery experience and recovery state evaluated by the questionnaire could be estimated from the halitosis data when waking up. The Kruskal-Wallis test was done to verify whether there was a significant difference between the questionnaire data and each feature. After that, for those with significant differences, multiple comparisons were performed using the Steel-Dwass Test.

First, because the subjects' answers were biased, especially few extreme answers, regarding the collected questionnaire data, those evaluated on a 5-grade evaluation were changed to a 3-class classification, and those evaluated on a 4-grade evaluation were changed to a 2-grade evaluation. On the 5-grade

[1] NOVENINE Co., Ltd. "SMASH": https://novenine.com/.

evaluation, 1 and 2 were regarded as 0, 3 was regarded as 1, and 4 and 5 were regarded as 2. On the 4-grade evaluation, 1 and 2 were regarded as 0, and 3 and 4 were regarded as 1.

Table 3. Kruskal-Wallis test on the questionnaire and each feature

Questionnaire	Measure	Class	Odor	Temperature	Humidity	Barometric pressure
Q-1	CO	3	-	$p < 0.05$	-	$p < 0.001$
Q-2	MA	3	$p < 0.05$	$p < 0.001$	-	$p < 0.001$
Q-3	PD	3	-	-	$p < 0.05$	$p < 0.001$
Q-4	CO	3	-	$p < 0.001$	-	$p < 0.05$
Q-5	PD	3	-	$p < 0.05$	$p < 0.05$	$p < 0.001$
Q-6	RE	3	$p < 0.05$	-	-	-
Q-7	MA	3	$p < 0.001$	$p < 0.001$	-	$p < 0.001$
Q-8	MA	3	$p < 0.001$	$p < 0.05$	-	$p < 0.05$
Q-9	CO	3	-	$p < 0.05$	-	$p < 0.05$
Q-10	PD	3	-	$p < 0.05$	$p < 0.001$	$p < 0.001$
Q-11	RE	3	-	-	-	$p < 0.05$
Q-12	RE	3	-	-	$p < 0.05$	-
Q-13	CO	3	-	$p < 0.05$	-	-
Q-14	PD	3	-	$p < 0.001$	-	-
Q-15	MA	3	$p < 0.001$	$p < 0.05$	$p < 0.05$	$p < 0.001$
Q-16	RE	3	-	$p < 0.05$	$p < 0.001$	$p < 0.001$
Q-17		3	-	$p < 0.05$	-	$p < 0.05$
Q-18		3	-	-	-	$p < 0.05$
Q-19		2	-	-	-	$p < 0.001$

"-" indicates that there is no significant difference in the feature among answers of the questionnaire ($p > 0.05$).

Next, the Kruskal-Wallis test was performed to verify whether there is a significant difference in each feature for each evaluation in the questionnaire. The results are shown in Table 3.

From this table, we describe the results for each measure of recovery. Regarding mastery, it was considered that there was a relatively significant difference between features other than humidity and question items. For each question item, multiple comparisons were performed using the Steel-Dwass Test. As a result, regarding Q-2, there was a significant difference in odor between 1 and 0 and between 1 and 2($p < 0.001$), and there was a significant difference in temperature and barometric pressure between 0 and 2($p < 0.001$). Regarding Q-7, there was a significant difference in odor between 1 and 0($p < 0.001$), and there was a significant difference in temperature and barometric pressure between 0 and 2($p < 0.001$). Regarding Q-8, there was a significant difference in odor and temperature between 2 and 0($p < 0.001$), and there was a significant difference in barometric pressure between 0 and 1($p < 0.01$). Regarding Q-15, there was a significant difference in odor and temperature between 0 and 1($p < 0.001$), and there was a significant difference in odor, temperature and barometric pressure between 0 and 2($p < 0.001$).

Regarding relaxation, there was not much significant difference in questions other than Q-16. In Q-16, as a result of multiple comparison using Steel-Dwass Test, there was a significant difference in temperature between 0 and 1($p < 0.01$), and there was a significant difference in temperature, humidity and barometric pressure between 0 and 2($p < 0.001$).

Regarding psychological detachment, there was a significant difference from each feature in Q-5 and Q-10. For these two questions, we performed multiple comparisons using the Steel-Dwass Test. As a result, regarding Q-5, there was a significant difference in odor, temperature, humidity between 1 and 0($p < 0.001$), and there was a significant difference in barometric pressure between 0 and 2($p < 0.001$). Regarding Q-10, there was a significant difference in temperature and humidity between 2 and 0($p < 0.01$), and also in barometric pressure between 2 and 0($p < 0.001$).

Regarding control, there was a significant difference between each question and temperature or barometric pressure, but there was no question that showed a significant difference as a whole.

Regarding the question about the recovery state, there was a significant difference between the evaluation value and the barometric pressure, but not so much from the other features.

Based on these, we thought that the answers of the questionnaire could be estimated by each features using numerical conditions, and constructed an estimation model using a random forest classifier.

Estimated questions are four questions for MA, Q-16 for RE, Q-5 and Q-10 for PD, and Q-4 for CO, which is the most influential question on this measure. Similarly, for the recovery state, we constructed a model that estimates the evaluation value of each questionnaire from halitosis data.

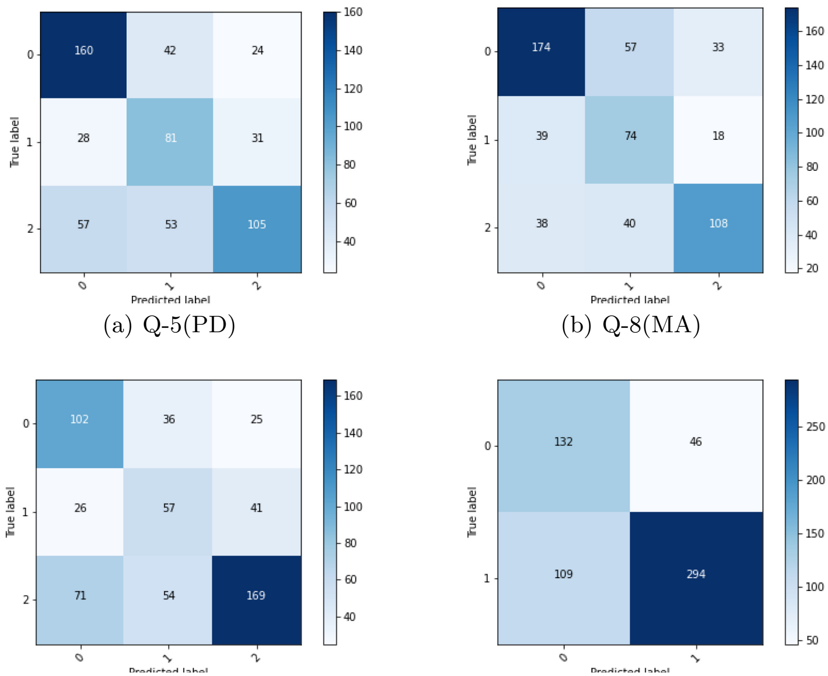
Table 4. Estimation score

Questionnaire	Measure	Class	Precision	Recall	f1-score
Q-2	MA	3	0.57	0.57	0.57
Q-4	CO	3	0.47	0.54	0.47
Q-5	PD	3	0.59	0.59	0.58
Q-7	MA	3	0.55	0.56	0.55
Q-8	MA	3	0.60	0.60	0.60
Q-10	PD	3	0.57	0.57	0.54
Q-15	MA	3	0.57	0.57	0.57
Q-16	RE	3	0.54	0.55	0.54
Q-17		3	0.51	0.54	0.50
Q-18		3	0.50	0.53	0.50
Q-19		2	0.71	0.74	0.71

5.3 Model Evaluation

We constructed a model to estimate the evaluation values of the questionnaire items described in the previous section from the collected halitosis data and verified by Leave-One-Person-Out Cross-Validation.

We evaluated the model using precision, recall, and f-score. Precision indicates the percentage of the results predicted by the model that were really correct. Recall indicates the percentage of the actual results that were predicted correctly. f-score is the harmonic mean of precision and recall.



(a) Q-5(PD) (b) Q-8(MA) (c) Q-16(RE) (d) Q-19

Fig. 3. Confusion matrix

The Table 4 shows the evaluation results.

For Q-4, which is a question about CO, we obtained an f-score of 0.47. We presumed that it was difficult to estimate because there was no significant difference in the features.

Q-8 had the highest score of the four questions about MA, with an f-score of 0.60. The Fig. 3(b) shows the confusion matrix of Q-8. This model rarely estimated that the true label of 0 is 2, and it can detect the state where MA is low.

Regarding the two questions regarding PD, Q-5 was a higher score, and its f-score is 0.58. The Fig. 3(a) shows the confusion matrix of Q-5. This model rarely estimated that the true label of 0 is 2, and it can detect the state where PD is low.

For Q-16, which is a question about RE, we obtained an f-score of 0.54. The Fig. 3(c) shows the confusion matrix of Q-16. It can be seen that the true label of 0 is hardly included in the prediction label of 2. If you do not have RE experience, you aren't presumed to have RE experience.

We describe the recovery state. For the mental and physical refreshing questions (Q-17, Q-18), an f-score of 0.50 was obtained. It is presumed that it was difficult to estimate because there was no significant difference in the features. For the question about sleep quality (Q-19), we obtained an f-score of 0.71. The Fig. 3(d) shows the confusion matrix of Q-19. It can be seen that the true label of 0 is hardly included in the prediction label of 1. If you have low sleep quality, this model doesn't predict your sleep quality is high.

5.4 Discussion

One of the purposes of this experiment was to verify whether the recovery experience and recovery state can be estimated from the halitosis data when waking up. We performed the Kruskal-Wallis test to verify whether there was a significant difference between the questionnaire data and each feature. As a result, we found that there was a relatively significant difference between halitosis features and MA. We also found that there was not much significant difference in CO. Some questions about the other two measures had a significant difference and others did not. Regarding the recovery state, there was no significant difference between mental and physical refreshment and halitosis features.

Based on these, we constructed an estimation model and validated it by Leave-One-Person-Out Cross-Validation to achieve the second purpose of this experiment that is to estimate the evaluation value of recovery from the halitosis data when waking up. As a result, our model detected the question of MA in the recovery experience with an f-score of 0.60, and the question of PD with an f-score of 0.58. Since This model rarely classifies inexperienced cases into experienced case, it is considered to be useful for detection when inexperienced case.

6 Conclusion

In this study, we focused on the tooth brushing that many people perform every morning and proposed a recovery estimation system from halitosis data collected by the natural flow of tooth brushing by the smart toothbrush. We extracted four features of odor, temperature, humidity, and barometric pressure from the breath blown by the user and constructed a model that outputs the evaluation value of recovery by Random Forest. To verify whether the halitosis data can be estimated for recovery and the proposed model, we experimented on 12 subjects.

In the experiment, we collected the halitosis from the prototype device of a smart toothbrush and the answers to the questionnaire about the recovery as the ground truth when the subjects woke up. As a result, we found a significant difference between the halitosis data and two measures of the recovery experience (MA and PD), and our three-value classification model detected MA with an f-score of 0.60, and PD with an f-score of 0.58. In addition, we considered that our model could firmly detect that the subjects have no recovery experience. From these results, a significant difference in halitosis for recovery was found. It was also shown that halitosis is useful for recovery estimation.

References

1. Bandura, A., Freeman, W., Lightsey, R.: Self-efficacy: the exercise of control. Br. J. Clin. Psychol. (1999)
2. Binnewies, C., Sonnentag, S., Mojza, E.J.: Daily performance at work: feeling recovered in the morning as a predictor of day-level job performance. J. Organ. Behav.: Int. J. Ind. Occup. Organ. Psychol. Behav. **30**(1), 67–93 (2009)
3. Brosschot, J.F., Pieper, S., Thayer, J.F.: Expanding stress theory: prolonged activation and perseverative cognition. Psychoneuroendocrinology **30**(10), 1043–1049 (2005)
4. Bui, A.L., Fonarow, G.C.: Home monitoring for heart failure management. J. Am. Coll. Cardiol. **59**(2), 97–104 (2015). https://doi.org/10.1016/j.jacc.2011.09.044
5. De Croon, E.M., Sluiter, J.K., Blonk, R.W., Broersen, J.P., Frings-Dresen, M.H.: Stressful work, psychological job strain, and turnover: a 2-year prospective cohort study of truck drivers. J. Appl. Psychol. **89**(3), 442 (2004)
6. Doi, Y., et al.: Psychometric assessment of subjective sleep quality using the Japanese version of the pittsburgh sleep quality index (PSQI-J) in psychiatric disordered and control subjects. J. Organ. Behav.: Int. J. Ind. Occup. Organ. Psychol. Behav. **97**, 165–172 (2000)
7. Etzion, D., Eden, D., Lapidot, Y.: Relief from job stressors and burnout: reserve service as a respite. J. Appl. Psychol. **83**(4), 577 (1998)
8. Inan, O.T., et al.: Novel wearable seismocardiography and machine learning algorithms can assess clinical status of heart failure patients. Circ. Heart Fail. **11**(1), e004313 (2018). https://doi.org/10.1161/CIRCHEARTFAILURE.117.004313
9. Ingram, S.S., et al.: The association between oral health and general health and quality of life in older male cancer patients. J. Am. Geriatr. Soc. **53**(9), 1504–1509 (2005)
10. Islam, S., Kim, A., Hwang, G., Song, S.H.: Smart tooth system for in-situ wireless PH monitoring. In: 2021 21st International Conference on Solid-State Sensors, Actuators and Microsystems (Transducers), pp. 755–758 (2021). https://doi.org/10.1109/Transducers50396.2021.9495706
11. Kim, S.Y., Sim, S., Kim, S.G., Park, B., Choi, H.G.: Prevalence and associated factors of subjective halitosis in Korean adolescents. PLoS ONE **10**(10), 14–21 (2015)
12. Kwon, H.J., Yoon, M.S.: Relationship of depression, stress, and self-esteem with oral health-related quality of life of middle-aged women. J. Dent. Hyg. Sci. **15**(6), 825–835 (2015)

13. Leng, L.B., Giin, L.B., Chung, W.Y.: Wearable driver drowsiness detection system based on biomedical and motion sensors. In: 2015 IEEE SENSORS, pp. 1–4 (2015). https://doi.org/10.1109/ICSENS.2015.7370355
14. Lim, H.R., Jeon, S.Y.: Relationship between stress, oral health, and quality of life in university students. J. Dent. Hyg. Sci. **16**(4), 310–316 (2016)
15. MarketsandMarkets Research Private Ltd: Wearable fitness technology market report. https://www.marketsandmarkets.com/Market-Reports/wearable-fitness-technology-market-139869705.html. Accessed 08 Sept 2021
16. Ministry of Health, Labour and Welfare: Compensation status for industrial accidents and public affairs accidents related to death from overwork. https://www.mhlw.go.jp/stf/newpage_04738.html. Accessed 08 June 2021
17. Ministry of Health, Labour and Welfare: Mental health measures and overwork measures in the workplace such as stress checks. https://www.mhlw.go.jp/bunya/roudoukijun/anzeneisei12/index.html. Accessed 08 Sept 2021
18. Ministry of Health, Labour and Welfare: Workmen's accident compensation status such as death from overwork. https://www.mhlw.go.jp/content/11402000/000796022.pdf. Accessed 08 Sept 2021
19. Ryotaro Bonai: Verification of blood glucose improvement effect through behavior change of IoT in type 2 diabetes: PRISM-J. https://www.amed.go.jp/content/000059276.pdf. Accessed 08 Sept 2021
20. Shetty, V., Morrison, D., Belin, T., Hnat, T., Kumar, S., et al.: A scalable system for passively monitoring oral health behaviors using electronic toothbrushes in the home setting: development and feasibility study. JMIR Mhealth Uhealth **8**(6), e17347 (2020)
21. Shimazu, A., Sonnentag, S., Kubota, K., Kawakami, N.: Validation of the Japanese version of the recovery experience questionnaire. J. Occup. Health **54**(3), 196–205 (2012)
22. Sonnentag, S., Fritz, C.: The recovery experience questionnaire: development and validation of a measure for assessing recuperation and unwinding from work. J. Occup. Health Psychol. **12**(3), 204 (2007)
23. Zhang, S., et al.: Necksense: a multi-sensor necklace for detecting eating activities in free-living conditions. CoRR abs/1911.07179 (2019). http://arxiv.org/abs/1911.07179