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Measuring Health Conditions Every Morning using a Smart Toothbrush with a Gas Sensor[1]

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Abstract. Mental illness is a serious health problem that the COVID-19 pandemic has exacerbated due to the new teleworking style. This work style forces isolation and reduces physical activities leading to a work efficiency drop and impaired work-life balance. Despite the current proliferation of IoT-based health measurement means, most of these devices are developed for physicians or cannot build a daily habit and keep the user's motivation due to design issues. Therefore, mental health measurement tools that can transparently assess the wellness of users daily basis are necessary. This paper proposes a mental health assessment system that smoothly integrates with the user's toothbrush providing a new generation of smart toothbrushes. Specifically, the designed system combines a gas sensor with the toothbrush for collecting halitosis data (odor, temperature, humidity, pressure) when brushing teeth. The collected data are then leveraged to train Random Forest models that estimate three indexes for two recoveries and one work engagement. To evaluate the proposed method, we collected realistic halitosis data using the smart toothbrush from 12 subjects every day over two months. The results show that the proposed system can obtain F-score of 0.84, 0.81, and 0.80 of Dedication, Vigor, and Absorption, respectively.

Keywords. recovery, work engagement, smart toothbrush, measurement system

1. Introduction

Mental illness is one of the most serious global health problems which is continuously increasing. The COVID-19 pandemic [1] has participated in raising the problem severity due to the new norms forced by the COVID, including remote working style, social distance, forced isolation, and/or reduced physical activity. All these policies were found to negatively affect physical and mental health leading to a drop in work efficiency and impairing work-life balance [2].

For this, enterprises and researchers on industrial insurance have taken other policies that ensure work engagement and recovery to ameliorate mental health and improve

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work performance. Recovery refers to the process of recovering from a stressed state [3]. It has been suggested that the process of recovery from work stress may be related to individual health and well-being and work performance [4]. Work engagement is defined as a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption [5]. Work engagement is related to a decrease in ill-health and increases in life satisfaction and job performance [6]. Therefore, regular and long-term checks focusing on recovery and engagement are important to work while healthy. However, the daily assessment system for such mental health has not been established.

Whereas, using IoT devices for measuring health conditions has 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. 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 [7].

In this study, to reduce the measurement burden on the user, we focus on the movements of daily life and aim to realize health measurement in a natural flow. One of the movements of daily life is brushing teeth, and people habitually do it when they wake up. Halitosis is said to correlate with stress; therefore, we assume it also relates to work engagement and recovery correlated with stress. This paper proposes a system that uses a smart toothbrush equipped with a gas sensor to collect halitosis and estimate daily recovery and work engagement by the natural flow during tooth brushing behavior when waking up. Since toothbrushes are necessary for daily life, using smart toothbrushes reduces the trouble of learning and managing special equipment for health measurement. In addition, monitoring daily mental state and work engagement leads to early detection of mental illness.

To evaluate the proposed method, we collected daily halitosis data of 12 subjects for approximately two months. Then, we constructed a machine learning 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 [8] [9] [6] [3] in / after tooth brushing. Then, we constructed three kinds of models that estimate each recovery and work engagement scale with two classes from the values of the questionnaire and compared the accuracy by leave-one-person-out cross-validation. As a result of the experiment, we achieved an F-score of 0.84, 0.81, and 0.80 in ”Dedication”, ”Vigor”, and ”Absorption”, which are indexes of Work Engagement, estimated by Random Forest with binary classification.

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 [10]. Zhang *et al.* [11] 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.* [12] 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.* [13] 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 percent on average in one year compared to conventional care for patients with type 2 diabetes. Inan *et al.* [14] provide remote monitoring of heart failure patients using wearable devices. Evaluating whether or not hospitalization is necessary for patients with heart failure using the lifelog of cardiac function collected from wearable terminals enables adjusting the treatment specific to the patient and reducing 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 harm users.

Bonai [7] examines the possibility of diabetes treatment using IoT, and it is expected that long-term utilization of IoT affects improving blood glucose. However, the IoT utilization rate without support will be low; more than 10 percent stop using it immediately after the introduction of IoT (within two weeks). Therefore, utilizing IoT devices for more than a year is not easy.

2.2. Relationship between oral condition and health

There are studies aimed at monitoring oral conditions. Shetty *et al.* [15] 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.* [16] 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 hand, 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 [17]. 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 [18].

A study also investigates the relationship between oral health and general health and quality of life in elderly male cancer patients [19]. 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 and work engagement.

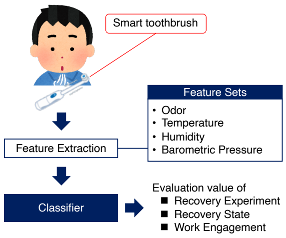

Figure 1. overview of the estimation model

Figure 2. a smart toothbrush “SMASH” developed by NOVENINE Co., Ltd.

3. Proposed Method

3.1. System Overview

In this study, we propose a system that collects halitosis and estimates recovery during tooth brushing that many people perform every morning. Generally, a dedicated device is required to collect halitosis, but we use a smart toothbrush that integrates brushing teeth and collecting halitosis in the proposed method. 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 two actions: to press the button on the toothbrush and blow for 3-5 seconds. Using halitosis collected from a smart toothbrush, users’ recovery and work engagement is estimated. There is a correlation between halitosis and poor lifestyle and stress [20], and we assume that there is also a correlation between recovery and halitosis. In this study, we search for features that correlate with recovery and work engagement and use them for estimation.

3.2. Estimation Model

Figure 1 shows the outline of the estimation model. The smart toothbrush collects the breath blown by the user and then, extracts four types of features, odor, temperature, humidity, and barometric pressure with 1Hz sampling rate. The halitosis value is calculated by the ratio of the maximum value and the minimum value of the resistance of the gas sensor value in one measurement. For temperature, humidity, and barometric pressure, the maximum value, minimum value, median value, and standard deviation in one measurement are taken as feature quantities. The maximum, minimum, median, and standard deviations of temperature, humidity, and barometric pressure are taken in as features.

The output of the model is a two-class evaluation of the sub-scales of recovery and work engagement. We use the questionnaire about the recovery and work engagement used in industrial insurance as the ground truth. We add up the evaluation values of the answered questionnaires for each scale. They are divided into two classes, one is larger than the center of the range that can be taken when the evaluation values are added up, and the other is smaller.

4. Questionnaire about Recovery and Work Engagement

We use the questionnaire about recovery and work engagement. Recovery refers to the process of recovering from a stressed state [3]. It has been suggested that the process of

Table 1. recovery experience questionnaire

I feel like I can decide for myself what to do.	CO
I learn new things.	MA
I forget about work.	PD
I decide my own schedule.	CO
I don't think about work at all.	PD
I kick back and relax.	RE
I seek out intellectual challenges.	MA
I do things that challenge me.	MA
I determine for myself how I will spend my time.	CO
I distance myself from my work.	PD
I do relaxing things.	RE
I use the time to relax.	RE
I take care of things the way that I want them done.	CO
I take time for leisure.	PD
I do something to broaden my horizons.	MA
I get a break from the demands of work.	RE

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

Table 2. recovery state questionnaire

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

Table 3. work engagement questionnaire

At my work, I feel bursting with energy	VI
At my job, I feel strong and vigorous	VI
I am enthusiastic about my job	DE
My job inspires me	DE
When I get up in the morning, I feel like going to work	VI
I feel happy when I am working intensely	AB
I am proud on the work that I do	DE
I am immersed in my work	AB
I get carried away when I'm working	AB

VI = Vigor , DE = Dedication , AB = Absorption

recovery from work stress may be related to individual health and well-being and work performance [4]. There are two indicators for recovery: (1) recovery experience and (2) recovery state. Work engagement is defined as a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption [5].

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.* [3]. The four measures are Psychological detachment, Relaxation, Mastery, and Control.

Psychological detachment means to leave work in a psychological sense. Relaxation is a measure related to leisure activities. Mastery refers to how much you are engaged in non-work activities such as rewarding experiences and learning opportunities. Control indicates the degree to which you can decide what kind of activity you want to do during your leisure time.

In this study, we use a questionnaire shown in Table 1 based on reference [3] [6]. 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 [8]. 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 [8] and the questions about sleep quality from Reference [9]. Reference [9] 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”.

4.3. Work Engagement

Work engagement is defined as a positive, fulfilling, work-related state of mind that is characterized by vigor, dedication, and absorption [5]. Work engagement is related to a decrease in ill-health and to increases in both life satisfaction and job performance [6]. Schaufeli *et al.* define vigor, dedication, and absorption [5]. Based on Schaufeli *et al.*, we explain them below. Vigor is characterized by high levels of energy and mental resilience while working, the willingness to invest effort in one’s work, and persistence even in the face of difficulties. Dedication is characterized by a sense of significance, enthusiasm, inspiration, pride, and challenge. Absorption is characterized by being fully concentrated and deeply engrossed in one’s work.

In this study, we use the Japanese version of the Utrecht Work Engagement Scale (UWES-9) to measure work engagement [21]. Table 3 shows the questionnaire items of UWES-9. These questionnaire items are evaluated on a 7-point scale from ”1: none” to ”7: always feel”.

5. Experiment

In this section, we describe the experiment to evaluate the proposed method. The purpose of this experiment is to verify estimating recovery and work engagement from halitosis data collected when waking up. The experimental period was two and a half months, and 12 subjects were recruited.

5.1. Data Collection

In this section, we describe how to collect data. To collect halitosis data, we used a smart toothbrush “SMASH” developed by NOVENINE Co., Ltd.[2], 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 seconds before tooth brushing. In addition, they answered the questionnaires shown in Section 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.

The questionnaire used as the ground truth was divided into two values for each index. About recovery experience and work engagement, the values of the questionnaires on each index were summed and classified according to whether they were larger or smaller than the median of the possible range. About the recovery state, the answers obtained with 4 or 5 values were divided into 2 values.

[2]NOVENINE Co., Ltd. “SMASH”: `https://novenine.com/`

5.2. Model Evaluation

This evaluation constructed and compared estimation models for each index using Support Vector Machine (SVM), K-Nearest Neighbor (KNN), and Random Forest (RF). For SVM and KNN, we selected the features with significant differences between the two classes based on a statistical test as inputs to model. For Random Forest, we used all features as inputs because the algorithm classifies based on feature importance. Table 4 shows the results of the Kruskal-Walis test for each index. We used all features with significant difference for each index.

We verified models by Leave-One-Person-Out Cross-Validation. We used F-score, the harmonic mean of precision and recall, to evaluate models. Precision indicates the percentage that the results predicted by the model were correct. Recall indicates the percentage of the actual results that were predicted correctly. The imbalanced data was adjusted by downsampling. Table 5 shows three types of model evaluations in the recovery experience. It can be seen that the F-score is high for Mastery and Psychological detachment. We assume that this is because many features have a significant difference between the classes of these two scales. In addition, F-score of the random-forest estimation is higher than that of the other models for all indexes. Table 6 shows three types of model evaluations in the recovery experience. The KNN estimation model has the highest F-score for sleep quality among the three measures, and the SVM estimation model has the highest F-score for mental refresh among the three measures. F-score of the random-forest estimation is higher than that of the other models for all indexes. Table 7 shows three types of model evaluations in the recovery experience. F-score in Dedication is the highest among the three indexes in any estimation model. We infer that many features that show significant differences between the two classes of Dedication are the factor. In addition, the estimation accuracy by random forest is high for all indexes.

Table 4. Kruskal-Wallis test on the questionnaire and each feature

index	features
Control	t_med, t_min, bP_med, bP_min, h_max, t_max, bP_max
Mastery	odor, t_med, t_min, t_max, bP_med, bP_min, bP_max
PD	h_med, h_min, h_max, bP_med, bP_min, bP_max
Relaxation	bP_med, bP_min, bP_max
Physical refresh	t_med, t_min, bP_std, bP_med, bP_min, t_max, bP_max
Mental refresh	bP_std, bP_med, bP_min, bP_max
Sleep quality	bP_med, bP_min , bP_std, bP_max
Vigor	h_med, h_min, h_max, bP_std, t_std
Dedication	odor, h_med, bP_min, bP_std, h_min, h_max, bP_max, bP_med
Absorption	h_med, h_min, odor, t_med, h_max, t_max

t = temperature , h = humidity , bP = barometricPressure

5.3. Discussion

Based on the results of model evaluation, the estimation by Random-Forest was shown to be the most useful among the three proposed models. In addition, considering the high estimation accuracy of random forest for all indexes, it is important to consider not

Table 5. F-score of recovery experience

	KNN	RF	SVM
Control	0.36	0.76	0.43
Mastery	0.55	0.79	0.54
PD	0.58	0.79	0.57
Relaxation	0.42	0.69	0.50

PD = Psychological detachment

Table 6. F-score of recovery state

	KNN	RF	SVM
Physical refresh	0.53	0.73	0.55
Mental refresh	0.46	0.73	0.57
Sleep quality	0.54	0.73	0.53

Table 7. F-score of work engagement

	KNN	RF	SVM
Vigor	0.50	0.81	0.60
Dedication	0.57	0.84	0.61
Absorption	0.41	0.80	0.50

RF = Random Forest

Table 8. data number of each class

	class 0 (low)	class 1 (high)
Control	75	467
Mastery	346	178
PD	220	307
Relaxation	117	421
Physical refresh	101	317
Mental refresh	101	323
Sleep quality	178	403
Vigor	325	143
Dedication	286	217
Absorption	279	200

PD = Psychological detachment

only the relationship between single features but also various relationships among them. Table 9, table 10, table 11 and table 12 show the confusion matrix in the estimation of the recovery experience by Random-Forest. For Control and Relax, we can see that the precision for 0 is low. This may be due to the biased number of data about Control and Relax. Table 8 shows the number of data for each class. We can see that the number of minority data is smaller for Control and Relax than for the other indexes. As for work engagement, table 8 shows that there is little difference in the number of data, and it is thought that the precision of a minority class did not decrease more than recovery experience and recovery state.

We also checked the importance of the features for the estimation model in the Random Forest. For the recovery experience, the importance of odor, humidity, and barometric pressure was high, while the importance of temperature was relatively low. In the statistical test, there was a significant difference in temperature, but the importance was not so large, which could be one of the reasons for the low accuracy in the estimation model by SVM and KNN. For the recovery state, no feature was considered to be outstandingly important compared to the other indexes. Therefore, we consider that the accuracy improvement needs more data and other features. In the case of work engagement, the importance of odor and humidity was large. The humidity showed a significant difference in the statistical test, which contributes considerably to estimating work engagement.

In general, even when there was no significant difference between the classes for a single feature, there were some features that had large importance in the Random forest and contributed to the improvement of accuracy. Therefore, it was shown that estimation by Random Forest using the features used in this study is effective in recovery and work

Table 9. Control

		Predicted Label	
		0 (low)	1 (high)
True	0	62	13
Label	1	67	400

Table 10. Mastery

		Predicted Label	
		0 (low)	1 (high)
True	0	296	50
Label	1	47	131

Table 11. PD

		Predicted Label	
		0 (low)	1 (high)
True	0	177	43
Label	1	66	241

Table 12. Relaxation

		Predicted Label	
		0 (low)	1 (high)
True	0	80	37
Label	1	93	328

Table 13. Physical refresh

		Predicted Label	
		0 (low)	1 (high)
True	0	81	20
Label	1	78	239

Table 14. Mental refresh

		Predicted Label	
		0 (low)	1 (high)
True	0	84	17
Label	1	82	241

Table 15. Sleep quality

		Predicted Label	
		0 (low)	1 (high)
True	0	130	48
Label	1	95	308

Table 16. Vigor

		Predicted Label	
		0 (low)	1 (high)
True	0	292	33
Label	1	42	101

Table 17. Dedication

		Predicted Label	
		0 (low)	1 (high)
True	0	264	22
Label	1	56	161

Table 18. Absorption

		Predicted Label	
		0 (low)	1 (high)
True	0	246	33
Label	1	60	140

engagement. In particular, F-score of over 0.80 was achieved for all measures of work engagement, which greatly contributed to the estimation of engagement from halitosis.

6. Conclusion

In this paper, we proposed a system that periodically estimates recovery and work engagement through tooth brushing, an activity of daily living. Based on the assumption that the effect of recovery and engagement in the previous day strongly appears to be the wake-up halitosis, the proposed system collects halitosis data by a smart toothbrush with a gas sensor and then estimates recovery and engagement scales.

To evaluate the proposed method, we collected halitosis data and questionnaires about recovery and work engagement from 12 subjects every day for approximately two months and constructed three models to estimate each index of the questionnaires based on the halitosis data. As a result, we achieved a F-score of 0.84, 0.81, and 0.80 in ”Dedication”, ”Vigor”, and ”Absorption”, which are indexes of Work Engagement, estimated by Random Forest with binary classification.

Our future work is the collection of minority data and the increase of the number of features. We are planning to continue our experiments with the smart toothbrush. In addition, we would like to increase the number of features that can be collected from daily life activities to further improve accuracy. Furthermore, we try to deal with individual differences by building a model for each individual.

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