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Feasibility of Emotion Recognition from Breath Gas Information

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***Abstract*— This paper proposes a smart gas sensing system to achieve emotion recognition using breath gas information. A breath gas sensing system is designed by using a quartz crystal resonator with a plasma-polymer film as a sensor. To collect breath gas data under emotional state, psychological experiments are carried out using a dental rise to excite emotions. In computational experiment of emotion recognition, two emotions of comfortableness and no emotion are considered and the machine learning-based approach such as an artificial neural network (ANN) and a support vector machine (SVM) is investigated. The obtained average emotion recognition rates are 47.5% using the ANN and 67.5% using the SVM, respectively. Experimental results show that using breath gas information is feasible and the machine learning-based approach is well suited for this task.**

I. INTRODUCTION

Psychological information, such as emotions, affections, and thinking process, recognized from nonverbal information plays an important role in human communication. For instance, people can communicate with each other more smoothly by using emotional information. It is clear that the exchange of nonverbal information is important in all forms of human communication and is sometimes more important than verbal information. This means that nonverbal communication is the basis of human communication. In addition to human-to-human communication, communication between humans and machines is becoming more and more common recently. To achieve more intimate and human-like interactions between humans and machines, a man-machine interface system would be required to recognize emotions of human.

Emotion recognition is an interesting but difficult task. People can recognize emotional speeches with about 60% accuracy and emotional facial expressions with about 70-98% [1]. Studies on emotion recognition with computers differ on the number of categories and the kinds of categories to use. Some emotion recognition systems in speech or facial expressions which have been treated several emotional states such as joy, teasing, fear, sadness, disgust, anger, surprise, and neutral. In those studies, emotions that are consciously and purposefully expressed by the subjects are treated since consciously expressed emotions are easier to recognize, control and significantly to gather data on, however recognition rates are 50-60% in emotional speech recognition [2], [3] and 80-90% in facial expressions [4], [5]. Physiological indexes are also useful to evaluate emotions since they can be measured physically and objectively and can be easily applied to engineering approaches. Physiological changes according to exciting emotions can be observed on changes of the body surface and/or autonomic nervous system [1]: e.g., skin conductivity, electrocardiogram, electromyogram, and blood volume pressure. Using brain waves seems to be effective [6], [7] since emotions are excited in the limbic system and are deeply related to cognition process. In these cases, however, sensors have to be attached to the human body to collect physiological data and expert techniques of handling the sensors are also required.

The other physiological index that expresses nonverbal information is biogas, such as breath and body odor. It might be considered that there is a relationship between mental states, such as emotion and stress, and physical states of the internal organs since feeling emotions affect the autonomic nervous system. From a viewpoint of relevance between illness and emotions such as a laughter and stress [8], it is shown that changes of the autonomic nervous system based on feeling emotions affect physical states of the internal organs recently. In contrast, studies on a disease diagnosis by breath gas test [9], [10], [11], [12] have been carried out actively in the field of remoteness medical care, telemedicine, and tele-care since it is clear that internal organs disease on a liver, lungs, and blood has bad breath (chemical features) from experience and an analytic chemistry point. As the breath gas test is a non-invasive method of biomarkers without pain, it protects the human body off from the risks of inserting electrodes or sensors. Thus, in a medical field, the breath gas test is expected as diagnosis technology to inspect an internal change of human body. In healthy person's breath, more than about 50 volatile components are already detected, and the relationship between illness and the outbreak mechanism of the volatile gas component is attracting attention. To achieve non-invasive monitor to the new bio-potential information by measuring the density of a very small amount of volatile gas component in breath gas and investigating its biochemical mechanism, development of a breath gas sensing and analysing system is necessary and the system requires high performance in analysis. On the other hand, oriental medicine explains the relationship between emotions and internal organs by using five elements (water, fire, wood, metal, and earth) theory of traditional Chinese philosophy: liver vs anger, heart vs joy, spleen vs worry, lungs vs sadness, and kidney vs fear. Although it is not commonly guaranteed that there exists such a relationship clearly yet, it might be possible to estimate emotions by using information of internal organs' states indicated by breath gas

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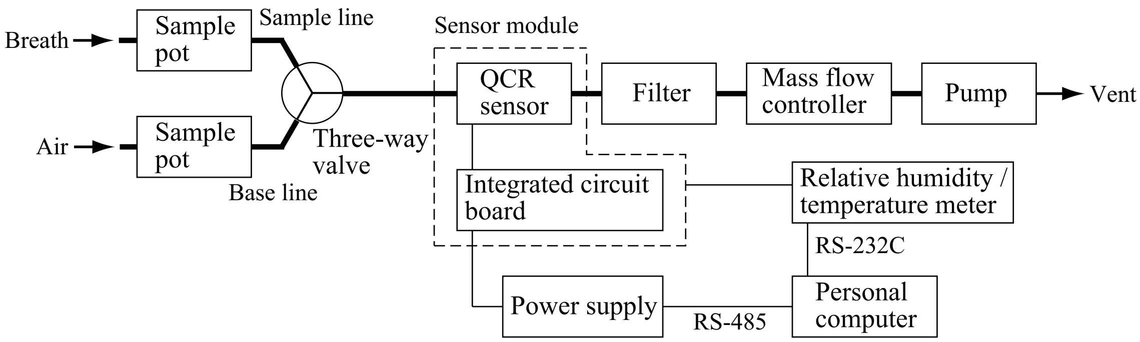

Fig. 1. Diagram of breath gas sensing system.

indirectly. Furthermore, if an evaluation method of mental states by using change of breath gas states can be achieved, information from the breath gas might provide a new man-machine interface. However, to date, few study of estimating mental states such as emotions from breath gas information has been undertaken. The relevance between breathing patterns and emotions has been studied [13], however, the relationship between breath gas information and emotions is not investigated. Therefore, we assume that emotions affect changes in the components of breath gas and investigate a possibility of using biogas emitted from a human body as a new channel of estimating human emotions [14], [15].

In this paper, we propose a breath gas sensing system and investigate emotion recognition by using machine learning-based approach as a first step to achieve emotion recognition from breath gas information. In section II, the basic design of breath gas sensing system utilizing a quartz crystal resonator sensor that is a type of mass transducer is described. In section III, collecting breath gas data using the sensing system under psychological experiments is carried out and some results of computational emotion recognition are presented.

TABLE I
MATERIALS FOR ORGANIC THIN FILM OF SENSOR CELL.

sensor cell	material
s1	D-phenylalanine
s2	D-tyrosine
s3	D-glucose
s4	DL-histidine
s5	Adenine
s6	Polyehylene (PE)
s7	Polychlorotrifluoroethylene (PCTFE)
s8	D-phenylalanine (Sealing)

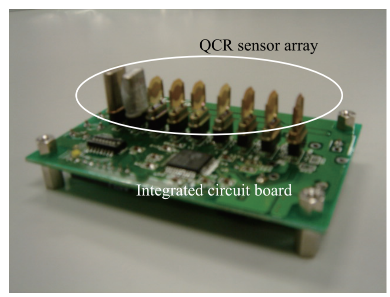

Fig. 2. Configuration of sensor module.

II. BREATH GAS SENSING SYSTEM

Figure 1 shows a block diagram of the breath gas sensing system. The sensor module utilized a sensitive sensor device based on a quartz crystal resonator (QCR) with a plasma-polymer film (PPF) where the sensor device can detect volatile organic compounds (VOCs) with parts-per-billion (ppb) levels under the dry air conditions [16], [17], [18]. The PPF was prepared by radio-frequency (RF) sputtering with an organic solid target, which was suitable for mass production and needed no reactive or toxic reagents for processing. A 9 MHz AT-cut QCR, which is 8.5 mm diameter and 0.1 mm thick, was used. As shown in Table I, the PPFs with different chemical structures were prepared by using various target materials including biomaterials (s1 $\sim$ s5) and synthetic polymers (s6 $\sim$ s7). The electrode's area of the sensor device was 0.13 cm^2. The relationship between the frequency shift of the QCR Δf (Hz) and mass variation of the organic thin film Δm (ng) is defined with Sauerbrey equation:

$$\Delta m = -1.05\Delta f \qquad (1)$$

The PPF-QCRs were placed in a flow sensor cell and simultaneously attached to an integrated circuit board equipped with a custom LSI for oscillation and resonant frequency measurements and a multiport serial interface as shown in Figure 2. This sensor module can mount eight PPF-QCRs.

Figure 3 shows the experimental setup for measuring and analyzing breath gas using arrays of PPF-coated QCRs in the laboratory. The sensor module was placed in a freeze sealing case. The relative humidity and temperature in the case were measured by a humidity sensor (HMT337, Vaisala, Finland, accuracy: $\pm 1.0\%$ for 0 to 90 % relative humidity). The breath measurement system consisted of two gas flow lines: a sample line carries breath gas and a reference line carries base gas. In our sensing system, air in indoor atmospheric condition was used as a reference or cleaning gas for establishing the initial state of the QCR sensors. Dehumidification by a molecular sieve and deodorization by a carbon were performed before atmosphere of the room was introduced into the reference line, and a sample pot was used as a buffer before introducing breath gas into the

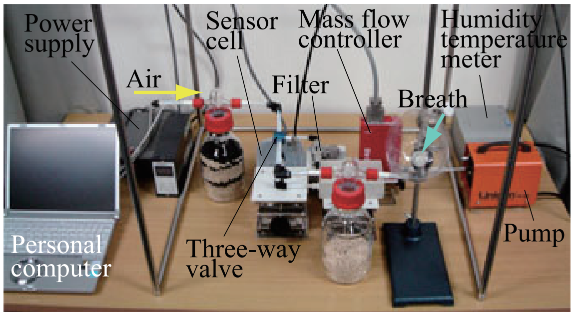

Fig. 3. Experimenal setup.

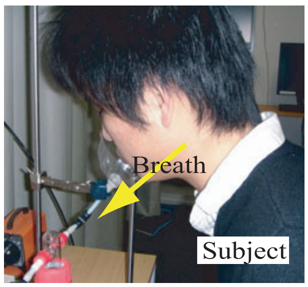

Fig. 4. Collection of breath gas.

sample line. The molecular sieve was also in the sample pot in order to dehumidify the sample gas. These flow lines were switched by a three-way valve to connect with the gas line of the sensor module. The flow rates of all flow lines were controlled around 200 mL/min generally by a mass flow controller (SEC-E40MK3, HORIBASTEC, Japan, accuracy: $\pm 1.0\%$ F.S., control range: 2 $\sim$ 100% F.S., flow range: 10/20/50/100/200/500 SCCM 1/2/3/5/10 SLM) and a dry vacuum pump (Linicon LV-125, NITTO-KOHKI, attainment vacuum level: -33.3 kPa, exhalation: 5 L/min). To remove minuteness mist in the gas line, an inline filter (FT4-5, GL Science, Japan, diameter: 5μm) was placed between the sensor module and the mass flow controller.

III. EXPERIMENTS OF COMPUTATIONAL EMOTION RECOGNITION

The responses of the breath gas sensing system were collected under the psychological experiments. By considering a guide to gathering physiological data for affective recognition described in the affective recognition work [1], the experiments were carried out following an *event-excited*, *lab setting*, *feeling*, *open-recording*, and *emotion-purpose* methodology. In this experiment, two emotions, such as comfortableness (refreshed, positive emotion) and no emotion, were considered. A subject used a dental rinse to excite the emotion, then the subject blew breath into the sample line of the sensing system as shown in Figure 4. Here, the subject covered her/his mouth with a nose pad and blew breath.

The experiments were carried out in our laboratory where the illumination, sounds, and room temperature were controlled to maintain uniformity. The experiments were done by 20 subjects of our laboratory (Japanese). In the experiment, the subject first blew her/his breath into the

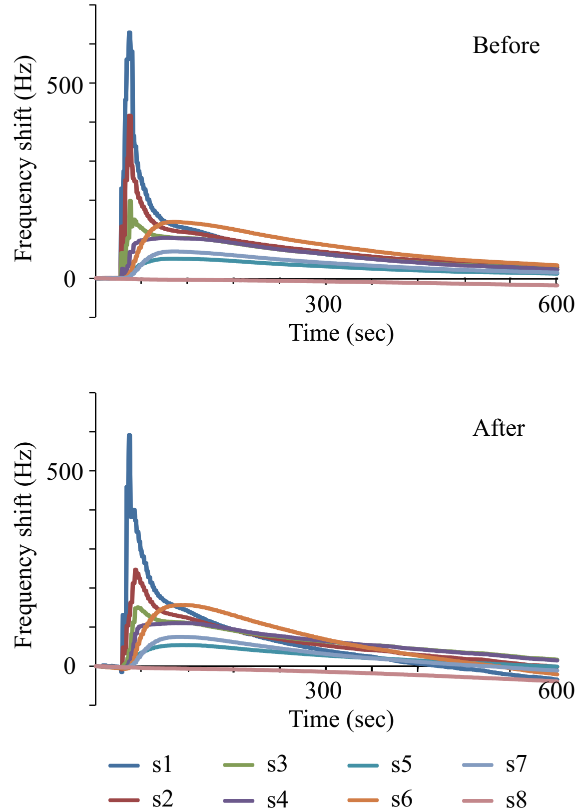

Fig. 5. Examples of responses from breath gas sensing system(top: before using dental rinse, bottom: after using dental rinse).

gas sensing system under no emotion after the baseline fluctuation of the QCR sensor array is suppressed. After 10 minutes interval, the subject washed her/his mouth with the dental rinse that is a commercial product (http://www.teamgum.net/eng/index.html/) and then blew her/his breath into the gas sensing system. The ingredients of dental rinse are: glycerin (wetting agent), polyethoxylated castor oil (surfactant), saccharin sodium salt (odor agent), tocopherol, cetylpyridinium chloride, triclosan (medical components), sodium citrate (pH controller), PCA ethyl cocoyl arginate (cleaning assistant), and ethanol. It can be considered that the volatility of these ingredients is very low (oils and sodium do not almost vaporize basically). Therefore, we assume that the dental rinse does not affect to the sensor response directly in this experiment although there might be the possibility that some ingredients are mixed into the vapor of breath. In collecting data from the QCR sensor array and the relative humidity/temperature sensor, the sampling rate was 1 second. The emotions of subjects were evaluated by using questionnaires based on the multiple mood scale[19].

Figure 5 shows examples of responses from each sensor cell. The horizontal axis is time and the vertical axis is the frequency shift. The subject blew breath to the sample line around 30 seconds, and the flow line was changed into the reference line around 90 seconds by the three-way valve. Except for the sensor 8, the response of the frequency

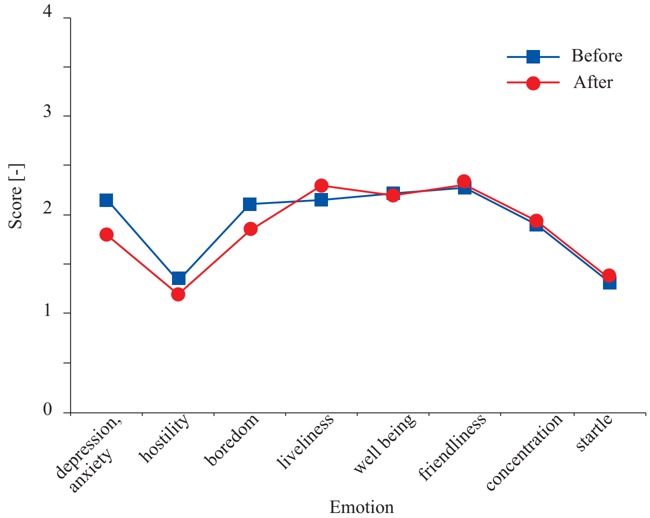

Fig. 6. Semantic profile obtained by multiple mood scale.

shift shows a local maximum after breath introduction and then converges to around zero as shown in Figure 5. The amplitude of each response curve depends on how strongly the subject blows breath to the sample line, however, the shape of the response curve is not affected.

In the questionnaires, 8 emotions, such as depression/anxiety, hostility, boredom, liveliness, well being, friendliness, concentration, and startle, were investigated before and after using the dental rinse. A semantic profile was utilized to evaluate the questionnaires. As shown in Figure 6, the semantic profile shows that the degrees of negative emotions (depression/anxiety, hostility, boredom) decrease while the degrees of positive emotions (liveliness, friendliness, concentration) increase after using the dental rinse. Therefore, we assume that the subject feel comfortableness/refreshed emotion by using the dental rinse.

To extract features from each response curve of sensor, principle component analysis (PCA) was introduced. The data matrix $\boldsymbol{M}_i$ of the subject i was defined by using all sensor data that are obtained during the interval of 30 seconds after the subject blows her/his breath as shown in Figure 7.

$$\boldsymbol{M}_i = \begin{bmatrix} s_1^{(i)}(1) & s_2^{(i)}(1) & \cdots & s_8^{(i)}(1) \\ s_1^{(i)}(2) & s_2^{(i)}(2) & \cdots & s_8^{(i)}(2) \\ \vdots & \vdots & & \vdots \\ s_1^{(i)}(k) & s_2^{(i)}(k) & \cdots & s_8^{(i)}(k) \\ \vdots & \vdots & & \vdots \\ s_1^{(i)}(30) & s_2^{(i)}(30) & \cdots & s_8^{(i)}(30) \end{bmatrix}$$

Here $s_j^{(i)}(k)$ is the jth sensor response of the subject i at the sampling time of k. The PCA was applied to the data matrix, and two principle components were calculated in the 8 sensors. Figure 8 shows the PCA score plot. The horizontal axis is the first principle component (PC1) while the vertical axis is the second principle component (PC2). The top of Figure 8 shows the PCA score plot obtained before using

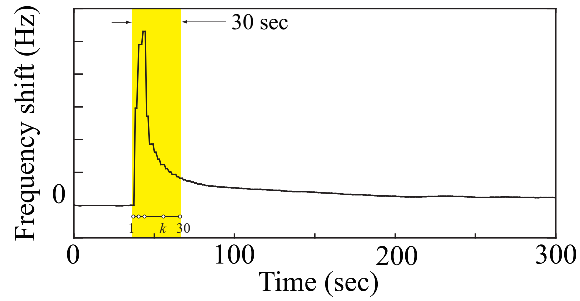

Fig. 7. Breath data period extraction.

dental rinse. The bottom of Figure 8 shows the PCA score plot obtained after using dental rinse. Here the results of all subjects are illustrated. The distribution of the PC2 is changed after using the dental rinse, however it is very small and depends on the subject. Since it is hard to find remarkable differences from the PCA score plot directly, the machine learning-based approach is introduced for the emotion recognition task.

The computational emotion recognition system was first designed by using artificial neural network (ANN), which is a multi layer feedforward network expressed by $\boldsymbol{y} = \boldsymbol{f}_{NN}(\boldsymbol{W}, \boldsymbol{x})$, where $\boldsymbol{x}$ is the input vector of ANN, $\boldsymbol{y}$ is the output vector of ANN, $\boldsymbol{W}$ is the weight parameters of ANN, and $\boldsymbol{f}_{NN}$ is the nonlinear mapping function approximated by the ANN. The input vector of ANN was composed with the first and second principle components of PCA results for all sensors as follows.

$$\boldsymbol{x}_i = \begin{bmatrix} pc_1^{s_1^{(i)}} & pc_2^{s_1^{(i)}} & pc_1^{s_2^{(i)}} & pc_2^{s_2^{(i)}} & \cdots & pc_1^{s_8^{(i)}} & pc_2^{s_8^{(i)}} \end{bmatrix}$$

where $pc_r^{s_j^{(i)}}$ is the rth principle component of the sensor j for the subject i. There were two neurons in the output layer of ANN. In the training process of ANN, the teaching signals $[\ y_{d_1} \quad y_{d_2}\ ]$ were defined as follows: the set of $[\ 1 \quad 0\ ]$ indicated comfortableness/refreshing emotion, and the set of $[\ 0 \quad 1\ ]$ indicated no emotion. The training of ANN was carried out according to the back-propagation algorithm and the training was quitted if the cost function $J = \frac{1}{2}\sum \|\boldsymbol{y_d} - \boldsymbol{y}\|$ achieved 10^{-5}. In the emotion recognition process, the output from ANN was investigated in decision logic that selects the best emotion based on the output values of ANN. The leave-one-out cross-validation method was used to evaluate the recognition ability of emotion recognition system.

Table II shows the emotion recognition result where a (16-12-8-6-2) network was used. The activation function of neuron was a linear function in both the input layer and the output layer. The sigmoid function was applied to the neurons of the hidden layers. The number of neuron in the hidden layers was determined by trial and error in order to converge the training of ANN. Though the recognition rate of 100% is achieved for the teaching data after the training of ANN is completed, the averaged recognition rate defined with the average of the diagonal element is 47.5% for the test

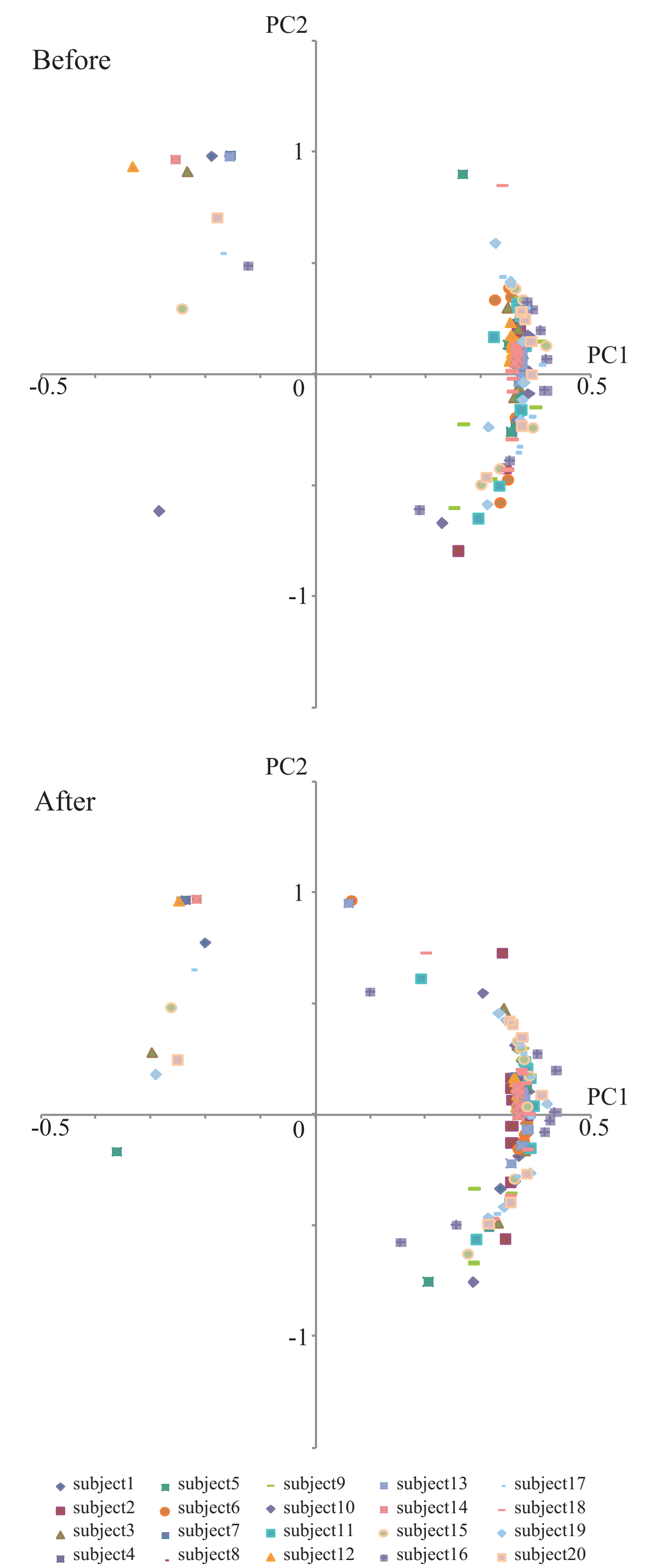

Fig. 8. Score plot of PCA (top: before using dental rinse, bottom: after using dental rinse).

data. The comfortableness/refreshed emotion can be attained the recognition rate of 55% while it is hard to recognise no emotion correctly. This result shows the feasibility of our

TABLE II

EMOTION RECOGNITION RESULTS USING ANN [%].

In \ Out	No emotion	Comfortableness
No emotion	**40**	60
Comfortableness	45	**55**

TABLE III

EMOTION RECOGNITION RESULTS USING SVM ($C = 1, \lambda = 100$) [%].

In \ Out	No emotion	Comfortableness
No emotion	**80**	20
Comfortableness	50	**50**

TABLE IV

EMOTION RECOGNITION RESULTS USING SVM ($C = 100, \lambda = 10$) [%].

In \ Out	No emotion	Comfortableness
No emotion	**70**	30
Comfortableness	35	**65**

TABLE V

EMOTION RECOGNITION RESULTS USING SVM ($C = 10^5, \lambda = 1$) [%].

In \ Out	No emotion	Comfortableness
No emotion	**55**	45
Comfortableness	40	**60**

emotion recognition system based on the ANN using breath gas information.

Next, the computational emotion recognition system was designed by using support vector machine (SVM). The SVM is originally designed for two-class classification and is finding the optimal hyperplane that minimizes the expected classification error of test samples by using statistical learning theory. Given a labelled set of training data $(\boldsymbol{x}_i, u_i)$ where $\boldsymbol{x}_i$ is the input vector ($\boldsymbol{x}_i \in R^N$) and y_i is the associated label ($y_i \in (-1, 1)$), the optimal hyperplane $\boldsymbol{w}\boldsymbol{x} + b = 0$ can be found by minimizing $\|\boldsymbol{w}\|^2 + C\sum_i \xi_i$ constrained by: $\xi_i \geq 0$ and $y_i(\boldsymbol{w}_i\boldsymbol{x} + b) \geq 1 - \xi_i$. Here ξ_i is the slack variable that is introduced to account for non-separable data, C is the margin parameter that quantifies the trade-off between training error and system capacity. Solving the quadratic programming problem, the optimal hyperplane can be defined by $g(\boldsymbol{x}) = \sum_i y_i \alpha_i^* K(\boldsymbol{x}, \boldsymbol{x}_i^*) + b^*$ where $K(\cdot, \cdot)$ is a kernel function, $\boldsymbol{x}_i^*$ is a support vector that corresponds to a nonzero Lagrange multiplier α_i^*, and b^* is a bias parameter. While the kernel function is a simple dot product for a linear SVM, a nonlinear function of the kernel function projects the data to high dimensional feature space in a nonlinear SVM and the optimal hyperplane is found in that space. In the emotion recognition process, the feature vector is fed into the SVM and the output from the SVM is investigated in the decision logic that selects the best emotion, and the class of the SVM indicates the recognition result.

In this experiment, the input vector of SVM was the same vector of the ANN. A gaussian function, $K(\boldsymbol{u}, \boldsymbol{v}) = \exp(-\lambda\|\boldsymbol{u} - \boldsymbol{v}\|)$, was used as the kernel function. The margin parameter C and function parameter λ were defined by trial and error in order to achieve complete classification rate for training data. Training and testing of the SVM were carried out by the leave-one-out cross-validation method. Tables III, IV, and V show the emotion recognition results. The maximum averaged recognition rate of 67.5% is achieved by using the SVM with $C = 100$ and $\lambda = 10$ as shown in Table IV.

IV. COCLUSIONS

This paper proposed a smart gas sensing system to achieve emotion recognition using breath gas information. A quartz crystal resonator with a plasma-polymer film was used as a sensor, and breath gas sensing system was designed under air in indoor atmospheric condition. The machine learning-based approach, such as the artificial neural network and the support vector machine, was conducted for computational emotion recognition and its characteristics were investigated. Psychological experiments were carried out using a dental rise to excite emotions and breath gas data under emotional state were collected from 20 subjects. In computational experiment of emotion recognition, two emotions of comfortableness and no emotion were considered and the obtained average emotion recognition rates were 47.5% using the ANN and 67.5% using the SVM, respectively. Experimental results demonstrated that using breath gas information is feasible and that the machine learning-based approach is well suited for this task.

There are many works to be done in the emotion recognition from breath gas information. In the sensing system, stabilization of the reference is required since the reference is easily affected from the air condition of the room. Improving how to introduce breath gas into the sensing-system is also important. Possible features of breath gas have to be selected in the feature extraction process, and further trials with different recognition methods may help improve recognition performance.

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