Classification of Red and White Wine by Smell Classification

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Abstract

Existing smell classification devices can display the strength of smells as quantitative values by using electric circuits. But they cannot perform the type of smells such that they are good or bad. In this paper, we construct a smell measurement system that can classify the type of smell by using neural networks and metal oxide semiconductor gas sensor arrays. In particular, we classify the kind of wines, which has been considered as the most difficult classification. We measure the smell data of white wine and red wine by using a method to change temperatures of smells of wine data and classify them by using a neural network. Using the classification rate of white wine and red wine, we consider the ability of classification of the proposed method.

1. Introduction

Recently, smell-sensing systems have become important developments. Currently, the devices used for the analysis of smell are gas chromatography and gas detector tube. In the case of gas chromatography, the maintenance of device itself is required, although it is high precision. In case of a gas detecting tube, although the device is not so large and maintenance is also unnecessary, it is thrown away and becomes rather expensive as a whole. There is also a way by human nose, in addition to it. The perfumer who is a specialist of smell classification actually smells and judges a smell. However, perfumer’s training takes time, its judgment may change in the condition at that time, and since it is not a quantitative technique, ambiguity appears [1][2]. Existing smell classification devices can display the strength of smells as quantitative values by using electric circuits. But they cannot perform the type of smells such that they are good or bad.

In this paper, we construct an electronic nose system that can classify the type of smell by using neural networks and metal oxide semiconductor gas sensor arrays. There are several commercial electronic nose devices currently in the world such as quality control of food industry, public safe-

Fig. 1 Sampling boxes.
We have combined these sensors and classify various smells. The working principle of MOGSs is explained in Fig. 2.

![Image of Oxidation and Reduction](image)

(a) Oxidation  (b) Reduction

Fig. 2 The principle of sensor.

This kind of sensor makes good use of oxidation-reduction reactions. As shown in Fig. 2, the potential barrier changes according to the existence or absence of gas. As a result, variable resistance becomes higher or lower. Since the output voltage changes to low or high, we can measure smell information by using a measurement circuit as shown in Fig. 3. Here, Rh is heater resistance and Rs is variable resistance. The resistance values are different for each sensor.

![Image of Odor Measurement Circuit](image)

Fig. 3 Odor measurement circuit.

3. Classification Method

We used the error back-propagation type neural network (BPNN) to classify odor as shown in Fig. 4. This method is one of multi-layered neural networks and the method uses the error between an output value and a desired value to the given input. Connection weights are changed so that the output error becomes minimum based on the gradient method [7][8]. The back-propagation algorithm is given by following steps.

Step1: Connection weights \( W_{jk}, W_{kj} \) are set a random number and \( \eta (>0) \) is set as an initial value.

Step2: Designate desired values of output \( \{d_k, k = 0,1, ..., K\} \), corresponding to the input data \( \{X_i, i = 0,1, ..., I\} \) in input layer.

Step3: Calculate outputs in hidden layer by the following formula:

\[
\text{net}_j = \sum_{i=0}^{I} W_{ji} X_i - \theta_j \text{O}_j = f(\text{net}_j), f(x) = \frac{1}{1 + e^{-x}}
\]

Step4: Calculate outputs in output layer by the following formula:

\[
\text{net}_k = \sum_{j=1}^{K} W_{kj} \text{O}_j - \theta_k, O_k = f(\text{net}_k), f(x) = \frac{1}{1 + e^{-x}}
\]

Step5: Calculate error \( e_k \) and generalization errors by the following formula:

\[
e_k = d_k - O_k \\
\delta_k = e_k O_k (1 - O_k) \\
\delta_j = \sum_{k=1}^{K} W_{kj} \delta_k \text{O}_j (1 - \text{O}_j)
\]

Step6: Calculate half of root mean square error of all outputs by the following formula:

\[
E = \frac{1}{2} \sum_{k=1}^{K} e_k^2
\]

Step7: If E becomes minimum, then finish the learning. Otherwise, coefficient weights are changed by the following formula:

\[
\Delta W_{kj} \equiv W_{kj}(t + 1) - W_{kj}(t) = \eta \delta_k \text{O}_j \\
\Delta W_{ji} \equiv W_{ji}(t + 1) - W_{ji}(t) = \eta \delta_j X_i
\]

After changing the connection weights, go to Step3.

![Image of Error Back-propagation](image)

Fig. 4 Error back-propagation.

4. Measurement Method

In case of Permeater, it was difficult to classify wines because of alcohol and water. Therefore, we thought a new method to remove components of alcohol and water. It is the method by changing the temperature. In the case, we used by Molecular Sieve of GL Science Co. LTD as smell adsorbent (Fig. 5). We measured white wine and red wine...
using the method. These are two ways to temperature changes. The first way is linear. The second way is step-by-step. In the way of linear, we aren’t able to obtain accurate smell information by changing the temperature rapidly. Therefore, we measure wines using by way of step-by-step. The measurement system is shown Fig. 6.

In this paper, a smell is measured in the procedure shown below.

(1) Dry air is flowed in the sampling boxes. A smell is flowed in the sampling boxes when an output voltage is stabilized.
(2) Raised to 100°C, 200°C, 300°C using by temperature control device and measure smell for each10 minutes(A corporation) . Raised to 100°C, 200°C, 250°C, 300°C using by temperature control device and measure smell for each 10 minutes(B or C corporation).
(3) After that, we transmitted the measurement results to the computer.

Here, we would like to confirm the component difference as the reason for difference in temperature.

![Figure of bottle](image1)

![Figure of Powder](image2)

### 5. Measurement Result

We measure red wines and white wines of A, B and C corporations. Each data are four. Measurement data of A, B and C corporations are shown Fig. 7.

![Red Wine of A Corporation](image3)
6. Select Feature Value

We used the peak as feature value at 100°C, 200°C, 250°C, 300°C. However, sensors of small reaction aren’t able to understand the peak. Therefore, we change a decibel for output voltage. The formula is given by following step.

\[ y_i = 20 \times \log_{10} V_i \quad (i=0, \ldots, 12) \]

The decibel values are output results. The sample result of change is shown Fig. 8. We remove sensor3 because of no change and normalized these data. We can expect to be a different by decibel conversion. We used the peak as feature value and performed classification using by BPNN of neural network.
7. Result

We classified the following case and showed conditions and results of these classifications. We explain about classification using by BPNN. \( \eta \) set 0.1[4]. Common conditions are shown Table 2. Here, we defined as follows: RA is Red wine of A corporation, WA is White wine of A corporation, RB is Red wine of B corporation, WB is White wine of B corporation, RC is Red wine of C corporation and WC is White wine of C corporation.

Table 2 Common condition

| Input Layer | 12 |
| Hidden Layer | 20 |
| Weight Coefficient | -0.3 ~ 0.3 |

(1) A and B corporation
We classified white wine and red wine of A and B corporations at 100°C and 200°C. The number of each data is four. The training data and the test data are 2. The network performed learning until the error was equal to \( 1.0 \times 10^{-2} \). Test data used 50 by changing parameters of neural network and changing the test data and training data. The results are shown in Table 3 and Table 4.

Table 3 Classification result of A and B corporations(100 °C).

| Smell data | RA | WA | RB | WB | Correct(%) |
| RA | 14 | 18 | 18 | 7 | 28 |
| WA | 19 | 27 | 3 | 1 | 54 |
| RB | 15 | 5 | 29 | 1 | 58 |
| WB | 12 | 15 | 14 | 9 | 18 |

Table 4 Classification result of A and B corporations(200 °C).

| Smell data | RA | WA | RB | WB | Correct(%) |
| RA | 9 | 21 | 19 | 1 | 18 |
| WA | 15 | 30 | 4 | 1 | 60 |
| RB | 6 | 4 | 36 | 4 | 72 |
| WB | 9 | 18 | 15 | 8 | 16 |

In these classifications, average classification rates are 38% and 42%. Classification rate of RA and WB is high. Therefore, we research detail of them. The results are shown Table 5 and Table 6.

Table 5 Classification result of WA and RB(100 °C).

| Smell data | RA | WA | Correct(%) |
| RA | 47 | 3 | 94 |
| WA | 34 | 16 | 52 |

Table 6 Classification result of B and C(200 °C).

| Smell data | RA | WA | Correct(%) |
| RA | 47 | 3 | 94 |
| WA | 23 | 27 | 54 |

In these classifications, average classification rates are 63% and 74%.

(2) B and C corporation
We classified white wine and red wine of B and C corporation at 250 °C. The number of each data is four. The training data and the test data are 2. The network performed learning until the error was equal to \( 1.0 \times 10^{-2} \). Test data used 50 by changing parameters of neural network and changing the test data and training data. The result is shown in Table 7.

Table 7 Classification result of B and C corporations.

| Smell data | RB | WB | RC | WC | Correct(%) |
| RB | 7 | 7 | 29 | 7 | 14 |
| WB | 10 | 20 | 10 | 10 | 40 |
| RC | 34 | 0 | 11 | 5 | 22 |
| WC | 15 | 13 | 15 | 7 | 14 |

In this classification, average classification rate is 23%. In 300°C, we didn’t be able to classify them because of no peak.

(3) Red wine and White wine
We classified red wine and white wine. The number of each data is twelve. The training data and the test data are 6. The network performed learning until the error was equal to \( 1.0 \times 10^{-2} \). Test data used 120 by changing pa-
Parameters of neural networks and changing the test data and training data. The result is shown in Table 8. In this classification, average classification rate is 68%.

Table 8 Classification result of red wine and white wine.

<table>
<thead>
<tr>
<th>Smell data</th>
<th>Red wine</th>
<th>White wine</th>
<th>Correct (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red wine</td>
<td>86</td>
<td>34</td>
<td>86</td>
</tr>
<tr>
<td>White wine</td>
<td>45</td>
<td>75</td>
<td>63</td>
</tr>
</tbody>
</table>

8. Conclusion and future works

In the classifications of (1) and (2), classification results of red wine and white wine were bad. However, in the Table 5 and Table 6, we are able to classify red wine of A corporation and white wine of B corporation roughly. Therefore, we think it is possible to classify wines of another corporation. In the classification of (3), the average classification rate was 68%. Therefore, we are able to classify them roughly.

In order to improve the classification results, we need to measure smell data of temperature change finely and change another smell adsorbent. We will measure many various wines and classify them using these methods in the future. We would like to create an artificial sommelier in the future.

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References


