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Automatic Evaluation of Sensory Information for Beer at a Fuzzy Level Using Electronic Tongue and Electronic Nose

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The flavor of beer is an important means of evaluating its quality. Beer flavor is the integrated embodiment of beer smell and taste information. In this work, the automatic evaluation of beer aroma, taste, and overall flavor sensory information was realized by a smell and taste sensor coupling array. First, a cloud model was used to realize the conversion between the descriptive language and the corresponding quantitative numbers in the process of beer sensory evaluation. Next, an electronic nose and an electronic tongue were used to test the quality of beer in terms of smell and taste. Finally, a fuzzy neural network was trained with the characteristic information collected by the sensor coupling array as the input, with a characteristic value generated from the conversion of the cloud model of sensory evaluation as the output. The results from this system are excellent, as the error rate in the overall fuzzy information evaluation of flavor was between 0.0048 and 0.0394.

1. Introduction

Over the past several years, beer has been one of the most popular products among consumers for its good taste and rich nutrition. On the other hand, the level of appreciation and quality requirement are increasing. Beer flavor is one of the means by which the quality of beer is commonly tested, and it represents the integrated embodiment of beer taste information (acidic, sweet, bitter) and smell information (scent). More than 800 flavor components are contained in beer, of which more than 100 are closely related to beer flavor. These components affect the quality of beer in a coordinated and comprehensive way.(1–3)

At present, testing and evaluation methods for beer quality include the traditional physical and chemical index detection methods, the sensory evaluation method, electronic nose detection, and electronic tongue detection.(4–7) The traditional physical and chemical index detection methods are widely used in production. For example, MALDI-TOF MS was applied to detect the acid and hop-shock-induced responses in beer.(8) In another approach, gas chromatography was used to analyze alcoholic beverages.(9) Ultra performance liquid chromatography was chosen to determine the ochratoxin A concentration in beer.(10) However, this method cannot achieve real-time detection, as

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it takes a long time to run. Moreover, this method cannot be used to represent the overall quality of beer, as its result is only an overview of some ingredients in the beer. The sensory evaluation method is also widely used in production. Complex instruments and equipment are not required by this method, and fuzzy information from human senses provided by descriptive language in the sensory evaluation is so crucial that it can provide a reference for research, direct development, and the degree of market acceptance of products.(11,12) However, sensory evaluation is subjective. The results vary with factors such as the taster's physical condition and mood changes, and the evaluation time is long while the efficiency is low. The electronic nose and electronic tongue, as two new detection methods, can be applied to alcoholic beverage concentrates for category detection, and their performance in this application is very good.(13–15) Ghasemi-Varnamkhasti *et al.* tested nonalcoholic beer and alcoholic beer using an electronic nose composed of six metal oxide sensors, and the accuracy of determining the category division was over 90%.(16) Cetó *et al.* used an electronic tongue to detect a total set of 51 samples of different brands and varieties, and the accuracy of determining the category division was over 80%.(17) There are two characteristics of alcoholic drinks: aroma and taste. Thus, detection using a single electronic nose or electronic tongue can only provide a subset of this information for alcoholic beverage samples.(18) Our research group classified eight different brands of Chinese liquor using the fusion technology of the electronic nose and electronic tongue, and compared the classification results with the single use of either electronic nose or electronic tongue. The comparison showed that the fault classification rate of the fusion technology is smaller than that obtained by the single use.(19) The applications of fusion improved the classification accuracy. However, the conclusions were still limited to only classification and could not be applied to predict the descriptive information corresponding to the sensory evaluation.(20,21) On the basis of the achievements made by other researchers, a relationship was set up between characteristic data collected by the sensor coupling array and the sensory evaluation of human preference in this study, so that the continued study and application have been further extended. The prediction of fuzzy information describing beer using beer beverage information, which is collected by the sensor coupling array, can be applied not only to achieve efficient automated testing but also to prevent the consumption of labor and material resources required to organize a sensory evaluation.

In this study, we proposed a method that can be used to predict beer aroma, taste, and the overall sensory information on flavor using a smell and taste sensor array. A cloud model was applied to realize the conversion between the descriptive language and the corresponding quantitative numbers in the process of beer sensory evaluation. A fuzzy neural network was trained with the characteristic information collected by the sensor coupling array as the input and with the characteristic value generated from the conversion of the cloud model of sensory evaluation serving as the output to realize the automatic and humanlike evaluation of beer based on information from sensory evaluation.

2. Measurement Systems

Two subsystems were included in the fusion system: the electronic nose and electronic tongue. Figure 1 shows the block diagram of the fusion system.

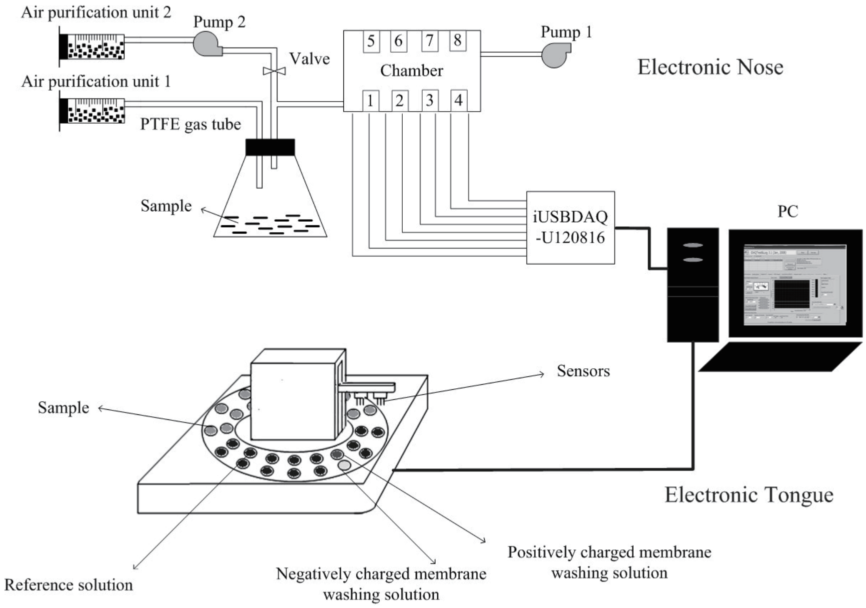

Fig. 1. Block diagram of the fusion system.

2.1 Electronic nose

The electronic nose has three main parts: the gas supply and transmitting unit, the sensor array and chamber unit, and the data acquisition and processing unit.

The first unit consists of an air purification device, the headspace of vials, and pumps with different flow rates. This unit is divided into two parts: gas injection and cleaning. In the gas injection part, pump one was opened and pump two was closed. Pump one was used to draw the sample gas into the chamber, which was then transported by the filtered air. In the cleaning part, both pump one and pump two were opened. Because the flow rate of pump two was higher than that of pump one, the cleaning air flow from pump two was used to purge the system, and the original gas flow direction at the inlet was inverted.(22)

Eight metal oxide semiconductor (MOS) sensors from Figaro Engineering, Inc. were used in this electronic nose. They were TGS-832, TGS-831, TGS-830, TGS-826, TGS-825, TGS-822, TGS-821, and TGS-813. They have a high sensitivity, a high stability, and a long lifetime, an even more specific output signal, and a simple conditioning circuit. The sensing element for such sensors is tin dioxide (SnO_2), which has a low conductivity in zero gas. When the concentration of the sensitive gas in the chamber increases, the sensor conductivity increases. Considering the retention of the sample gas in the chamber, the chamber was composed of cardboard covered by polytetrafluoroethylene (PTFE). PTFE is a thermoplastic polymer, its melting point is 327 °C, its density is 2.2 g/cm^3 and its friction coefficient is 0.05–0.10.(23) The resistance of PTFE to Van der Waals forces means that the adsorption of gas to PTFE is low. Thus, PTFE was chosen to reduce gas adsorption in the chamber. In the electronic nose, the entire gas tubing was also made of PTFE.

In the third unit, an IUSBDAQ-U120816, developed by HYTEK Automation, was chosen to collect the data. It has eight single-ended, 12-bit analog inputs. It can convert the 0–5 V analog voltage output signals into digital signals and send the digital signals to the computer.

2.2 Electronic tongue

The electronic tongue is a new analytical instrument, which is also known as the intelligent bionic system of taste. In this study, an SA-402B electronic tongue (Insent Inc., Japan) was used. The tongue contains a sensor made of an artificial lipid membrane, which is similar to the taste cells of a human tongue. The electronic tongue can be used not only to evaluate the basic gustatory sensory indexes objectively but also to analyze the bitter, astringent, and fresh aftertaste.[24]

In this study, five taste sensors and two reference electrodes were used in the electronic tongue experiment. The five taste sensors were the saltiness sensor CT0, the sourness sensor CA0, the bitterness sensor C00, the astringency sensor AE1, and the umami sensor AAE. Five basic gustatory sensory indexes (bitterness, astringency, sour, salty, and sweet) and two aftertastes (bitter and astringency) were selected.

3. Experimental Section

3.1 Experimental materials

Five commercial beers were chose as samples, which were purchased at a local supermarket. Their alcohol content, original wort concentration, raw materials, and location of production were copied from the beer bottle labels. Table 1 lists all of these.

3.2 Measurement

There were two steps in our experiment: the electronic nose and electronic tongue measurements.

The dynamic headspace sampling method was used in the electronic nose measurement. The laboratory conditions were controlled at 20 ± 2 °C and 65 ± 5% relative humidity. There were three steps in each experiment. First, zero gas, which was processed with activated carbon, was vented into the chamber for 30 min so that the signal of the response of the sensors to zero gas could achieve a minimum stable value. Second, a 100 ml beer sample was introduced into the airtight jar, and pump one was opened for approximately 4 min so that the volatile substances in the beer sample could enter the airtight jar and achieve a saturated state. Third, pump one and pump two were opened at the same time for approximately 20 min to purge the airway and air cell with zero gas, which was processed with activated carbon. When the response of the sensor recovered to the lowest stable value, a new measurement was started.

Table 1
Characteristics of sampled beers.

Number	Alcohol content	Original wort concentration	Raw and auxiliary materials	Location
1	≥ 4.3%vol	11%	Water, malt, rice, hops	Zhaoqing City, Guangdong Prov.
2	≥ 4.3%vol	11%	Water, malt, rice	Shenyang City, Liaoning Prov.
3	≥ 4.3%vol	11%	Water, malt, rice, hops	Beijing City
4	≥ 2.5%vol	8%	Water, malt, corn, wheat malt, hops	Changchun City, Jilin Prov.
5	≥ 3.6%vol	9.7%	Water, malt, rice, hops	Wuhan City, Hubei Prov.

The electronic tongue adopted for this experiment was SA-402B, which is mainly composed of taste sensors, a signal acquisition unit, and a pattern recognition part. The device was equipped with five taste sensors and two reference electrodes. Data were collected at room temperature. Before data collection, the electronic tongue system ensured the reliability and stability of data by going through steps of self-checking, diagnosis, and correction. At the beginning of each experiment, electrodes were cleaned for 90 s in a reference solution, then for an additional 120 s in a second reference solution. When the output reached a balance, a measurement was begun, lasting for 30 s. After the measurement, electrodes were cleaned in another two reference solutions for 3 s, then the aftertaste value was measured.

The experiments have been carried out with 18 samples of each kind of beer, and each sample was measured by the electronic nose and electronic tongue in accordance with the above steps. Five kinds of beer were measured, so we got 90 groups of data. When the dataset was used for comparison with the cloud model and the training of the fuzzy neural network, it is essential to the following analysis.

3.3 Sensory evaluation experiments

Sensory evaluations adopt the method of quantitative description. Forty human sensory evaluation staff members were selected through the sensory evaluation ability test, in which each staff member was considered capable of distinguishing the tastes of interest. An appropriate training of the sensory evaluation staff resulted in a relatively consistent understanding of the evaluation standards and the sensory evaluation system.

This experiment included five different brands of beer according to the two aspects of aroma and taste, and the overall flavor of each beer was evaluated. Weighting values set for the references and expert opinions on aroma and taste were 0.40 and 0.60, respectively.(25) Forty sensory evaluation staff members evaluated the three sensory properties of each beer sample in turn, yielding 40 groups of effective sensory evaluation scores.

4. Results and Discussion

4.1 Cloud model processing of sensory evaluation data

In the process of beer artificial evaluation, the quality of beer was characterized with descriptive language. However, the evaluation language specification used by the trained staff can be grouped. The cloud model can realize any conversion between descriptive language and specific numbers.(26–28) The specific numbers means three characteristic values which represent the sample's overall features. So that the information of beer sensory evaluation could be used to set up a relationship with the characteristic data collected by the sensor coupling array.

Here, we analyze only the two-dimensional cloud model of aroma and taste. The forty groups of information of sensory evaluation, namely, the corresponding cloud droplets x obtained for beer aroma and taste, are converted into three characteristic values, expected E_x, entropy E_n, and hyperentropy H_e, using the two-dimensional reverse cloud model.

$$E_x = \sum_{i=1}^{N} x_i / N \tag{1}$$

$$E_n = \sqrt{\pi/2} \cdot (1/N) \cdot \sum_{i=1}^{N} |x_i - \bar{x}| \tag{2}$$

$$H_e = \sqrt{[1/(N-1)] \cdot \left| \sum_{i=1}^{N} (x_i - \bar{x})^2 - E_n^2 \right|} \tag{3}$$

In these equations, E_x represents a certain concept of beer sensory evaluation; E_n represents the numerical range ambiguity of the qualitative concept (i.e., it indicates the cloud droplet size accepted by the qualitative concept in the number field space, revealing the random nature of the qualitative concept); H_e represents the entropy of the beer entropy E_n, for measuring randomness and fuzziness; and N is the total number of samples.

Values of E_x, E_n, and H_e obtained from sensory evaluation data from different beers are shown in Table 2. Among the five beers, the E_x values of the aroma and taste in beer 1 were the largest, showing that beer 1 had a clearly discernable hops aroma and its taste was pure. The E_x values of the aroma and taste in beer 4 were the smallest, indicating that the hops aroma of beer 4 was not readily discernable and that the sample had a firm texture. The E_n value of taste in beer 1 was 5.4754, which was the largest among the five beer samples, showing that the cloud droplet group range accepted by the qualitative concept in beer 1 was the highest and that randomness and fuzziness were high. The E_n value of taste in beer 2 was the smallest, showing that the cloud droplet group range was the lowest and that randomness and fuzziness were low. The H_e value of aroma in beer 4 was the smallest, showing that the description by the sensory evaluation staff for this sample was the most consistent and that the results of the sensory evaluation were stable. The H_e value of taste in beer 2 was the largest, showing that the result of sensory evaluation was unstable and that there was divergence in the descriptions of the sample by the sensory evaluation staff.

The E_x, E_n, and H_e values, obtained from the forty groups of sensory evaluation data could be used to recover features of the sensory evaluation data related to aroma and taste sensory data of any number of groups of five samples. A selection of codes from the positive cloud model algorithm in Matlab is presented as follows:

Table 2
Output of the two-dimensional backward cloud model for the beers.

Number		E_x	E_n	H_e
1	Aroma	20.1000	2.6790	2.1938
	Taste	22.6500	5.4754	2.8471
2	Aroma	14.4250	2.5998	4.8150
	Taste	16.5500	2.2638	6.2142
3	Aroma	17.0250	2.9179	4.3704
	Taste	16.6750	2.5497	5.7495
4	Aroma	5.8250	4.1540	0.2857
	Taste	9.1500	2.5865	5.9747
5	Aroma	16.5500	3.8179	3.8876
	Taste	16.0500	2.8560	5.6382

(1) $x' = normrnd(E_n, H_e, 1, N)$; generated N normal random numbers using E_n as the expectation and H_e as the variance.
(2) $x(k) = normrnd(E_x, x', 1)$; generated one normal random number using E_x as the expectation and x' as the variance; the number was a specific quantitative value of qualitative concept A, namely, one cloud droplet. The repeated calculation of this step, for $k = 1, 2,..., N$, yielded N cloud droplets in total.
(3) $y(k) = \exp[-(x(k) - E_x)^2 / (2x(k)^2)]$; calculated the degree of membership of each cloud droplet to qualitative concept A.

The values of E_x, E_n, and H_e are obtained from the forty groups of sensory evaluation data and could recover any group of sensory evaluation results for the aroma and taste scores of the five beer samples using the two-dimensional positive cloud model generator. The forty groups of restored sensory evaluation data for the aroma and taste of the five beer samples are shown in Figs. 2(a1)–2(a5). The scatter diagrams of the original effective aroma and taste evaluation information obtained from the sensory evaluation experiments are shown in Figs. 2(b1)–2(b5). The recovered cloud droplets were consistent with the basic characteristics of the original sensory evaluation data in Fig. 2. The data points of beer 1 are on the top right, as the scores of aroma and taste were high. The data points of beer 4 are on the bottom left, as the scores of aroma and flavor were low. The remaining points were dispersed in the middle area. The conversion process between the beer qualitative concepts and specific numbers retained the characteristics of the samples. Thus, the cloud model could be used to realize any uncertain transformation between the descriptive language and specific value expression in the process of beer sensory evaluation.

4.2 Predictive information on beer sensory evaluation based on a fuzzy neural network

Fuzzy neural networks are a new type of pattern recognition algorithm. They combine the advantages of fuzzy theory and neural networks, have a strong adaptive capacity, and can be combined with fuzzification.[29,30] The fuzzy neural network adopted in this study was composed of an input layer, a fuzzification layer, a fuzzy rule layer, a fuzzy decision-making layer, and an output layer.

The input layer is mainly aimed at reading and normalizing data collected by the sensor array according to different smell and taste characteristics. Each node of this layer connects to the input vector of each component directly, playing a role in delivering the accurate collected value to the next layer of the fuzzy neural network. The beer sample input layer of this study contains 15 input nodes ($n = 15$), corresponding to the 8 sensor characteristic signals of the electronic nose sensor array and the 7 sensor characteristic signals of the electronic tongue sensor array. The fuzzification layer is designed for the implementation of the fuzzification of the input layer. This study adopted Gaussian membership functions based on the beer sample features. There were $2n + 1$ hidden nodes selected (i.e., there were 31 hidden nodes). Every node of the fuzzy rule layer is a fuzzy rule that matches former fuzzy rules to determine the fitness of each rule. The fuzzy decision-making layer is used for the comprehension of later fuzzy rules. The output layer is the output of the whole fuzzy neural network, corresponding to the predictive values of beer aroma, taste, and sensory evaluation information of overall flavor characteristics.

A selection of the core formulas applied in this paper are as follows:

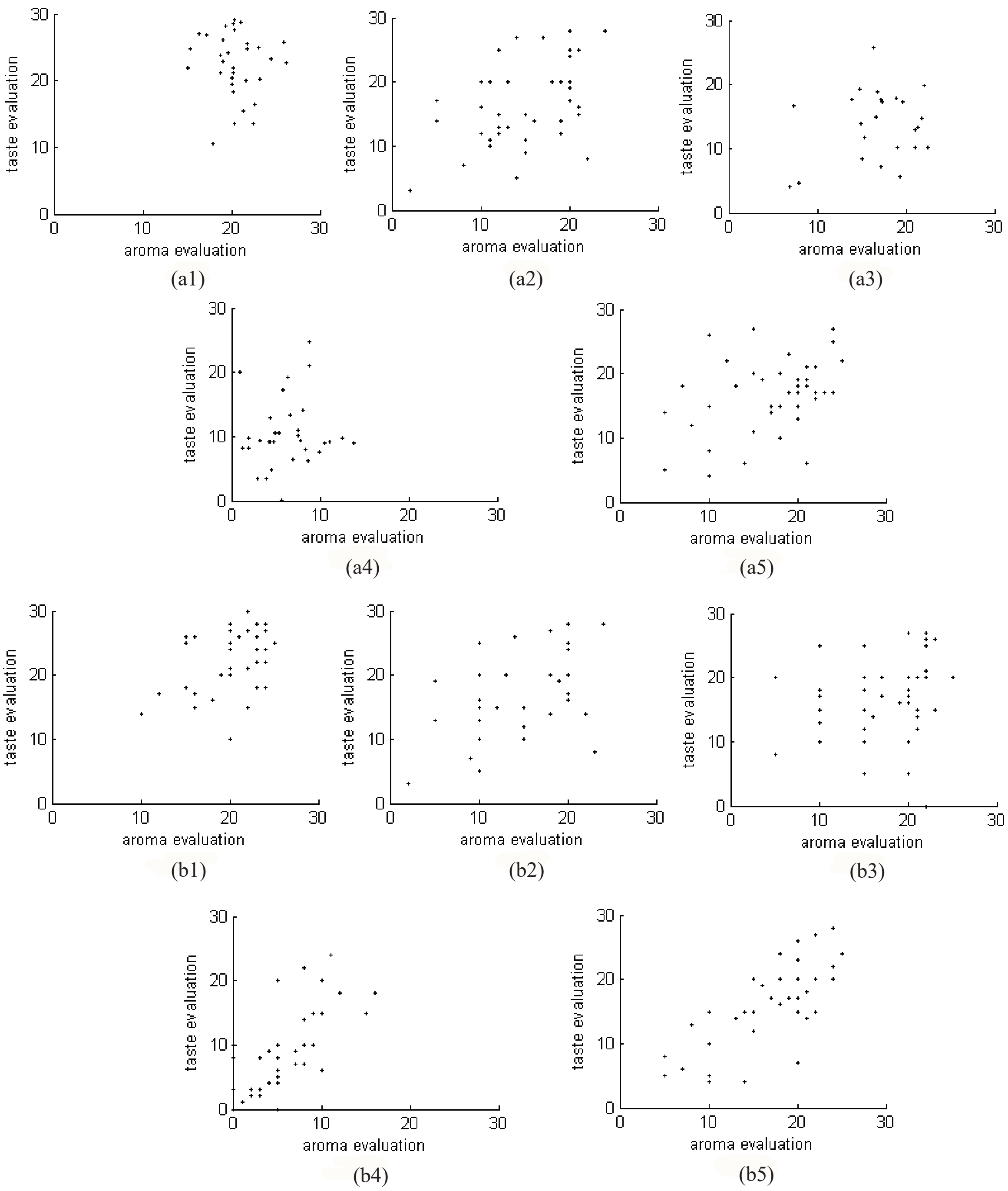

Fig. 2. Restored and original aroma and taste evaluations of beers 1 through 5: (a1)–(a5) restored aroma and taste evaluation of beers 1 through 5, (b1)–(b5) original aroma and taste evaluation of beers 1 through 5.

$$u(i, j) = \exp\left[-\left(x(i) - c(j, i)\right)^2 / b(j, i)\right], \tag{4}$$

where $i = 1, 2,..., n$; $j = 1, 2,..., 2n + 1$; $u(i, j)$ is the membership degree of each input component in the fuzzification layer relevant to the fuzzy set of variable values of sensory evaluation; $c(j, i)$ is the center value of the fuzzification layer; and $b(j, i)$ is the node width of the fuzzification layer.

$$w(j) = \prod_{i=1}^{n} u(i,j) = \exp\left\{-\sum_{i=1}^{n}\left[(x(i) - c(j,i))^2 / b(j,i)\right]\right\} \quad (5)$$

$$addv = sum(w) \quad (6)$$

$$addyw = \sum f_i w^{\mathrm{T}}(j) \quad (7)$$

Here, $\sum f_i = p(0) + p(1)x(1) + ... + p(i)x(i) + ... + p(n)x(n)$; $w(j)$ is the fitness degree of each rule in the fuzzy rule layer; and $w^{\mathrm{T}}(j)$ is the transposed vector of $w(j)$. The vector after the transposed vector composed of the elements $p(i)$ contains the regulation parameters of the fuzzy decision-making layer.

$$y = addv/addyw, \quad (8)$$

where y is the output of the fuzzy neural network.

The fuzzy neural network was used to predict the sensory evaluation information of beer aroma, taste, and overall flavor characteristics. In this study, the experiments obtained 90 groups of data each using the electronic nose and electronic tongue; the data were divided into 2 subsets randomly, and each subset had 45 sets of data. One subset was considered as the test set, and the rest as the training sets. The prediction curve of taste E_x values for the five beer samples is shown in Fig. 3, the sample numbers 1–9 on the X-axis belong to beer 1, samples 10–18 belong to beer 2, samples 19–27 belong to beer 3, samples 28–36 belong to beer 4, and samples 37–45 belong to beer 5. The actual output means the true E_x value of five kinds of beer samples, and the predicted output means the prediction value that was obtained by the fuzzy neural network model. The prediction of characteristic values could describe the characteristics of beer flavor and recover features of the sensory evaluation data; thus, it realized the humanlike prediction of beer flavor. Predicted results described by the relative error rate are shown in Table 3. In terms of aroma, the relative error rate

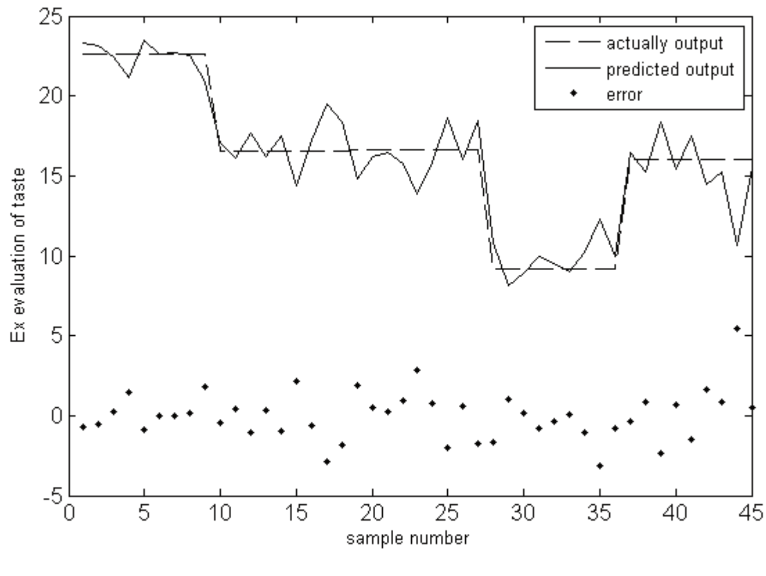

Fig. 3. E_x prediction curve for taste.

Table 3
Relative error rate in beer taste prediction.

Number		E_x	E_n	H_e
1	Aroma	0.0265	0.0287	0.0884
	Taste	0.0256	0.0606	0.0452
	Overall flavor	0.0048	0.0266	0.0304
2	Aroma	0.0588	0.0206	0.0404
	Taste	0.041	0.0580	0.0274
	Overall flavor	0.0394	0.0205	0.0256
3	Aroma	0.0421	0.0247	0.0822
	Taste	0.0628	0.0715	0.0243
	Overall flavor	0.0112	0.0221	0.0144
4	Aroma	0.0813	0.0234	0.0559
	Taste	0.0820	0.0590	0.0348
	Overall flavor	0.0230	0.0098	0.0275
5	Aroma	0.0457	0.0428	0.0622
	Taste	0.0839	0.0993	0.0519
	Overall flavor	0.0136	0.0283	0.0208

of H_e values in beer 1 had a maximum value of 0.0884. In terms of taste, the relative error rate of E_n values in beer 5 had a maximum value of 0.0993. In summary, when predicting a single feature of aroma or taste, the relative error rate was between 0.0206 and 0.0993. The predictive accuracy was high, as the relative error rate of the flavor information as a whole reached 0.0062. The effect of the whole set of flavor evaluation information was adequate. The relative error rate was controlled between 0.0048 and 0.0394.

5. Conclusions

In this study, an automatic evaluation system was promoted; this system completed the mapping between the characteristic information collected by a sensor coupling array and the descriptive language from sensory evaluation through a combination of cloud model and fuzzy neural network. It realized the humanlike evaluation of beer flavor other than mere classification. First, the conversion between descriptive language and quantitative data was achieved for the beer evaluation using a cloud model. Then, the relationship between the beer sensory evaluation data and characteristic data collected by the sensor coupling array was expressed. A test of beer quality from the two aspects of smell and taste using an electronic nose and an electronic tongue was proposed and discussed. Finally, the fuzzy neural network was trained with the characteristic information collected by the electronic nose and electronic tongue sensor coupling array as the input and information from the cloud model transformation of sensory evaluation information as the output. When predicting the beer sensory evaluation information using this fuzzy neural network, the error rate was between 0.0048 and 0.0993, and the overall flavor information error rate was even lower than 0.0394, thereby an automatic evaluation system of beer sensory information is acceptable.

The electronic tongue and electronic nose were successfully able to describe the category of food including beer in the last year; at this point, we are only dissatisfied with classification. The beer sensory evaluation information, which was automatically predicted by the electronic nose and electronic tongue sensor coupling array in a fuzzy level, may attract the attention of the beer industry.

Acknowledgements

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