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International Journal of Pharmaceutics 305 (2005) 13–21
international journal of pharmaceutics
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Evaluation of the taste and smell of bottled nutritive drinks

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Received 17 June 2005; received in revised form 8 August 2005; accepted 10 August 2005
Available online 10 October 2005

Abstract

The purpose of this study was to evaluate the palatability of 15 bottled nutritive drinks, all commercially available in the Japanese market, using data from artificial taste and odor sensors. In gustatory sensation tests, well-trained healthy volunteers were asked to score the drinks in terms of palatability and of the four basic tastes. The results suggest that overall palatability is positively correlated with sourness intensity and fruitiness ($R = 0.82$ and 0.86, respectively) and negatively correlated with bitterness intensity and the tasting of medicinal plants ($R = -0.85$ and -0.80, respectively).

The sourness and bitterness intensity could be predicted by taste sensor and fruitiness could be predicted by odor sensor, respectively.

By performing principal component analysis of the taste sensor data, the 15 drinks could be classified into four groups. The group classified as being predominantly sour had the highest palatability score, 3.8. By principal component analysis of odor sensor data, the drinks could also be classified into four groups and this time the group with a fruity flavor (smell) showed the highest palatability score, 3.4. In the combined analysis of both taste and odor data, products containing medicinal plants showed the lowest palatability. Finally, the combined usage of the taste and odor sensors gave rise to a three-group classification. Thus, not only the taste sensor but also the odor sensor may be useful in evaluating the palatability of bottled nutritive drinks.

Keywords: Taste sensor; Nose sensor; Sourness; Bitterness; Medicinal plant; Nutritive drinks

1. Introduction

Many bottled nutritive drinks are available in the Japanese market for indications, such as chronic fatigue, to aid recovery, to maintain nutrition in patients with weak constitutions or chronic illness, and for supplementation of nutrients. These drinks contain many different combinations of ingredients, including vitamins, minerals, amino acids, and active components of medicinal plants, and consequently differ considerably in taste. The taste and odor of bottled nutritive drinks greatly influence their palatability, and several

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doi:10.1016/j.ijpharm.2005.08.019

different approaches have been made to achieve satisfactory flavoring or taste-masking of these drinks, as their palatability has been shown to be directly correlated with marketability.

The artificial taste sensor has been used to evaluate objectively not only taste but also odor. It has been used in various trials to determine the taste characteristics of foods, or beverages, such as beer, sake, green tea, etc. (Toko, 1998; Tan et al., 2001; Taniguchi and Ikezaki, 2001). We have previously demonstrated the usefulness of the taste sensor in predicting the bitterness of medicines (Uchida et al., 2001; Nakamura et al., 2002; Ishizaka et al., 2004). In recent years, sensor-array-based aroma analysis technology has been developed that complements human sensory analysis. This technology, the so-called "nose sensor", utilizes an array of electronic chemical sensors with partial specificity and an appropriate pattern-recognition system, capable of recognizing simple or complex odors (Gardner and Bartlett, 1994). Many applications in the food industry, for flavor or odor analysis of meat, grains, coffee, beer, fruit, and edible oils, have already been published (Strassburger, 1997; Shaller et al., 1998; Giese, 2000; Chauvet et al., 2000; Stephan et al., 2000; Natale et al., 2002; Jonsdottir et al., 2004). Few applications have been made in the pharmaceutical field, although the nose sensor has been used for flavor analysis of a pharmaceutical liquid oral formulation (Zhu et al., 2004). Ohmori et al. (2005) evaluated odor in tablets containing L-cysteine, a drug with an unpleasant odor, and demonstrated the odor-masking ability of thin-layer sugarless-coated tablets.

In the present study, we examined the taste and odor of 15 commercially available bottled nutritive drinks, using human gustatory sensation tests and artificial taste and odor sensors. In the gustatory sensation tests, intensity scores ranging from 1 to 5 were given for overall palatability, for nine components of palatability (astringency, good aftertaste, tasting of a medicinal plant, fruitiness, refreshing, seeming beneficial, irritating to the throat, pungency, and the desire to drink again), and for the four basic tastes (sweetness, saltiness, sourness, and bitterness).

When evaluated using a taste sensor, there was a positive linear correlation between the intensity of sourness measured by the sensor and the overall palatability determined in human gustatory tests, and a negative linear correlation between the intensity of bitterness and overall palatability. Sourness and bitterness were therefore predictable using taste sensor data. When nose sensor data were evaluated, there was a positive linear correlation between the intensity of fruitiness and overall palatability, and a negative linear correlation between the intensity of tasting of a medicinal plant and overall palatability. Fruitiness and tasting of a medicinal plant were therefore predictable using nose sensor data. Finally, principal component analysis of the sensor data, alone or in combination, was used in further data analyses.

2. Experimental

2.1. Materials

The 15 bottled nutritive drinks used in the present study are listed in Table 1. Four of the products are marketed by six different companies, represented by the letters A–F in the right-hand column. Six products (S2, S6, S7, S8, S11, and S13) contain thiamine derivatives and thiamine. Four products (S9, S10, S14, and S15) contain medicinal plant ingredients, S9 and S10 containing two or three medicinal plants and S14 and S15 containing 7–13 different plants.

Table 1
The commercially available bottled nutritive drinks used in the study

Trade name	Company name
S1	A
S2[a]	B
S3	C
S4	D
S5	E
S6[a]	B
S7[a]	B
S8[a]	F
S9[b]	D
S10[b]	F
S11[a,c]	B
S12[c]	C
S13[a,c]	F
S14[b]	E
S15[b]	C

[a] Products containing thiamine derivative ingredients.
[b] Products containing medicinal plant ingredients.
[c] Tired eye and stiff shoulders.

2.2. Gustatory sensation tests

Gustatory sensation tests were carried out using seven well-trained volunteers. The palatability scores were evaluated by standard deviation (S.D.) method as follows: seven subjects were asked to score samples on the basis of the following nine items, using a five-point symmetrical scale representing both extremities of the item (1, extremely; 2, slightly; 3, neither; 4, slightly; 5, extremely). The items were: (1) not astringent/astringent; (2) no aftertaste/strong aftertaste; (3) weak taste of medicinal plant/strong taste of medicinal plant; (4) not fruity/fruity; (5) not refreshing/refreshing; (6) does not seem beneficial/seems beneficial; (7) not irritating to throat/irritating to throat; (8) not pungent/pungent; and (9) do not want to drink again/want to drink again.

Before testing, the volunteers were asked to keep sample solutions of standard bitterness in their mouths for 10 s, and were told their bitterness scores (from 1 to 5).

In the evaluation of four basic tastes, gustatory sensation tests were performed according to the method of Katsuragi et al. (1997), using sucrose at concentrations of 29.2, 87.7, 187.1, 409.4, and 994.2 mmol/L as a standard for sweetness, sodium chloride at concentrations of 20.5, 51.3, 130.0, 273.8, and 616.0 mmol/L as a standard for saltiness, tartaric acid at concentration of 0.17, 0.60, 1.73, 4.66, and 11.99 mmol/L as a standard for sourness, and quinine sulfate at concentration of 0.003, 0.0012, 0.031, 0.078, and 0.201 mmol/L as a standard for bitterness. Scores of 1–5 were allocated to increasing concentrations of all the standard solutions. After tasting a 2 mL sample of an unknown bottled nutritive drink, the volunteers were asked to score the sample on a scale of 1–5 for the four basic tastes (sweetness, saltiness, sourness, and bitterness), for overall palatability, and for the nine components of palatability (see above and Table 2). All samples were kept in the mouth for 10 s. After tasting each sample, subjects gargled well and waited for at least 20 min before tasting the next sample.

Table 2
Relationship between overall palatability and four basic intensities and individual palatability

Correlation with palatability	
Astringency	−0.62 ($p < 0.050$)
Good aftertaste	0.80 ($p < 0.005$)
Tasting of medicinal plant	−0.80 ($p < 0.001$)
Fruitiness	0.86 ($p < 0.001$)
Refreshing	0.70 ($p < 0.005$)
Seem to be beneficial	−0.77 ($p < 0.001$)
Irritation to throat	−0.68 ($p < 0.010$)
Pungency	−0.65 ($p < 0.001$)
Want to drink again	0.92 ($p < 0.0001$)
Sweetness	0.40 ($p < 0.100$)
Sourness	0.82 ($p < 0.001$)
Bitterness	−0.85 ($p < 0.001$)
Saltiness	−0.33 ($p < 0.500$)

2.3. Sensor measurement and data analysis

2.3.1. Taste sensor

The taste sensor system, ‘α-ASTREE’ Liquid and Taste Analyzer of Alpha M.O.S., Toulouse, France, was used to measure the electronic potential of the bottled nutritive drinks. The ‘α-ASTREE’ Liquid and Taste Analyzer consists of an array of seven liquid cross-sensitive electrodes or sensors (ZZ1, BA1, BB1, CA1, GA1, HA1, and JB1), a 16-position autosampler, and associated interface electronic module. Each sensor consists of a silicon transistor with an organic coating that determines the sensitivity and selectivity of the sensor. This set was found to provide good characteristics and to permit the differentiation of the majority of food groups and pharmaceutical products. A measurement consists of the electric potential difference between each sensor and the Ag/AgCl reference electrode in the equilibrium state at room temperature. Thus, an integral signal for each sample comprised a vector with seven individual sensor determinations. Four measurements were performed for every sample and the mean and standard deviation were calculated. The data were analyzed with S-PLUS 2000J (Mathematical Systems Inc., Tokyo, Japan).

2.3.2. Nose sensor

All samples were analyzed on a Fox 4000 nose sensor (Alpha M.O.S.) equipped with metal oxide sensors with a headspace autosampler HS100. A sensor diagnostic check was performed weekly using the sensor diagnostics kit provided by the manufacturer.

The measurement conditions were as follows: sample 1 mL; vial volume 10 mL; incubation temperature on headspace generation 60 °C; incubation time on headspace generation 15 min; agitation speed of a vial on headspace generation 500 rpm; injection volume 100 μL. The detector includes 18 different metal oxide sensors divided into three chambers. There are three types of sensors: T, P, and LY. Types T and P are based on tin dioxide (SnO_2), but have different sensor geometries. LY sensors are chromium–titanium oxides (Cr_2–$x$$Ti_x$$O_3 + y$) and tungsten oxide ($WO_3$) sensors. Multiple types of sensor are used in the instrument to ensure adequate sensitivity and selectivity. Odorants first adsorb to the sensors and then react with the metal oxide sensors, depending on the type of sensor and the molecular functionality of the odorant. The reaction changes in sensor resistance are monitored and output as raw signals. The sensors are regenerated by reaction with oxygen in the carrier gas after each injection. To simplify the data processing, only the maximum resistance changes of each sensor are used for analysis. In this study, the sensors LY/LG, LY/G, LY/AA, LY/gH, LY/gCT1, LY/gCT, T30/1, P10/1, P10/2, P40/1, T70/2, PA2, P30/1, P40/2, P30/2, T40/2, T40/1, and TA2 were used for the evaluation of the degree of unpleasant odor. The data were analyzed with S-PLUS 2000J (Mathematical Systems Inc.).

3. Results and discussion

3.1. Relationship between overall palatability and palatability components in human testing

The correlation between the overall palatability score and the nine components of palatability obtained in human gustatory studies is shown in Table 2. Strong positive correlations were found between the overall palatability score and scores for “fruitiness”, “refreshing”, “good aftertaste”, and “want to drink again” ($R = 0.86$, 0.70, 0.80, and 0.92, respectively), while negative correlations were found with scores for “pungency”, “astringency”, “tasting of a medicinal plant”, “seeming beneficial”, and “irritating to throat” ($R = -0.65$, -0.62, -0.80, -0.77, and -0.68, respectively). Palatability was therefore most positively correlated with “fruitiness”, and most negatively correlated with “tasting of a medicinal plant”, which relates to the odor.

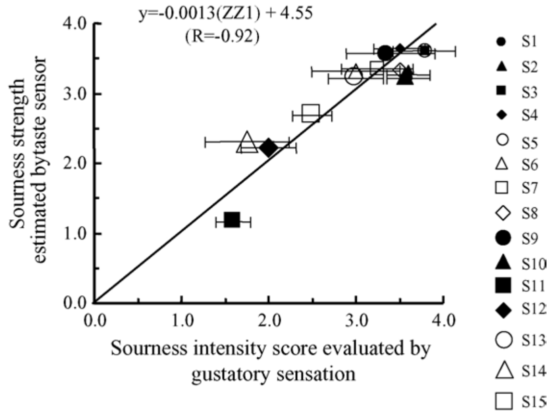

Fig. 1. Relationship between sourness intensity scores obtained in human gustatory tests and those predicted by a taste sensor. The values are given as the mean ($n = 7$) plus standard error. ZZ1 represents the relative value of sensor array 1.

3.2. Relationship between overall palatability and the four basic tastes in human testing

Table 2 also shows the relationship between the overall palatability score and four basic tastes (sweetness, saltiness, sourness, and bitterness) determined in the human gustatory tests. There was a high correlation between overall palatability and the sourness of drinks ($R = 0.82$), while there was a clear negative correlation between overall palatability and bitterness ($R = -0.85$). Acidity greatly affects the overall palatability of bottled nutritive drinks, which can be improved by the addition of flavors containing sour substances (organic acids such as citric acid) (Miyanaga et al., 2003; Mukai et al., 2004).

3.3. Prediction of sourness or bitterness intensity by taste sensor

Fig. 1 shows the relationship between the sourness scores obtained in gustatory sensation tests and the predicted sourness intensity calculated from taste sensor output channel ZZ1. The derived regression equation was $y = -0.0013(\text{ZZ1}) + 4.55$ ($R = -0.92$), where the y-axis and x-axis are the predicted taste sensor value and observed gustatory sourness score, respectively. The sourness of nutritive drinks is assumed to be due to content of an organic acid (e.g., citric acid, D,L-malic acid, or tartaric acid). The products for tired eyes and

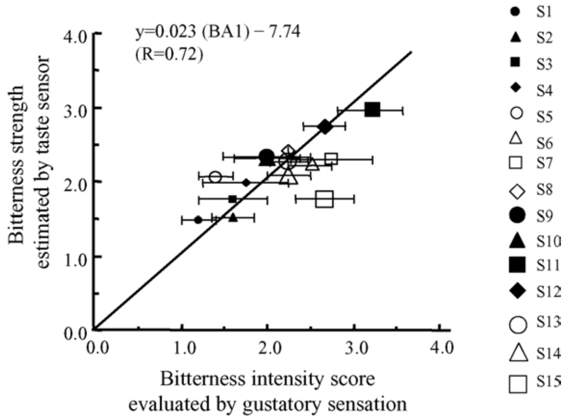

Fig. 2. Relationship between bitterness intensity scores obtained in human gustatory tests and those predicted by a taste sensor. The values are given as the mean ($n = 7$) plus standard error. BA1 represents the relative value of sensor array 2.

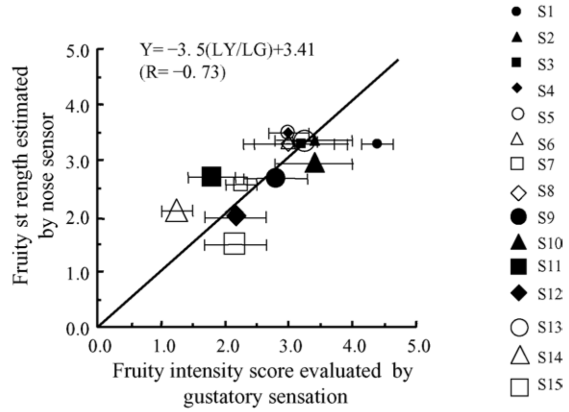

Fig. 3. Relationship between fruity intensity scores obtained in human gustatory tests and those predicted by a nose sensor. The values are given as the mean ($n = 7$) plus standard error. LY/LG represents the relative value of sensor array 1.

stiff shoulders (S11, S12, and S13) were the least sour, and the output from channel ZZ1 for these products shows the highest negative correlation with the sourness intensity scores obtained with organic acids.

Fig. 2 shows the relationship between the bitterness scores obtained in gustatory sensation tests and the predicted bitterness intensity calculated from taste sensor output channel BA1. The derived regression equation was $y = 0.023(\text{BA1}) - 7.74$ ($R = 0.72$), where the y-axis and x-axis represent the predicted taste sensor value and observed gustatory bitterness score, respectively. Product S11 was the most bitter of the bottled nutritive drinks, most probably due to its relatively high content of thiamine derivatives. The drinks which contained a lot of medicinal plants were also regarded as bitter.

3.4. Prediction of the intensity of fruitiness or medicinal plant taste by a nose sensor

The correlation of the scores of the evaluation items "fruitiness", which showed a positive correlation with overall palatability, and "tasting of a medicinal plant", which showed a negative correlation, was predicted by the nose sensor. Fig. 3 shows the relationship between the "fruitiness" scores obtained in gustatory sensation tests and the predicted fruity intensity calculated from nose sensor output channel LY/LG. The derived regression equation was $y = -3.5(\text{LY/LG}) + 3.41$ ($R = -0.73$), where the y-axis and x-axis represent the predicted nose sensor value and observed gustatory "fruitiness" score, respectively.

Fig. 4 shows the relationship between the "tasting of a medicinal plant" scores obtained in gustatory sensation tests and that predicted by nose sensor output from channel LY/LG. The derived regression equation was $y = 5.6(\text{LY/LG}) + 1.43$ ($R = 0.86$), where the y-axis and x-axis represent the predicted nose sensor value and observed gustatory test results of the "tasting of a medicinal plant" score, respectively.

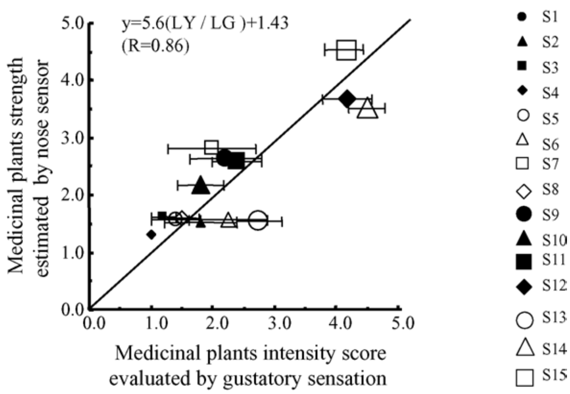

Fig. 4. Relationship between 'tasting of a medicinal plant' intensity scores obtained in human gustatory tests and those predicted by a nose sensor. The values are given as the mean ($n = 7$) plus standard error. LY/LG represents the relative value of sensor array 1.

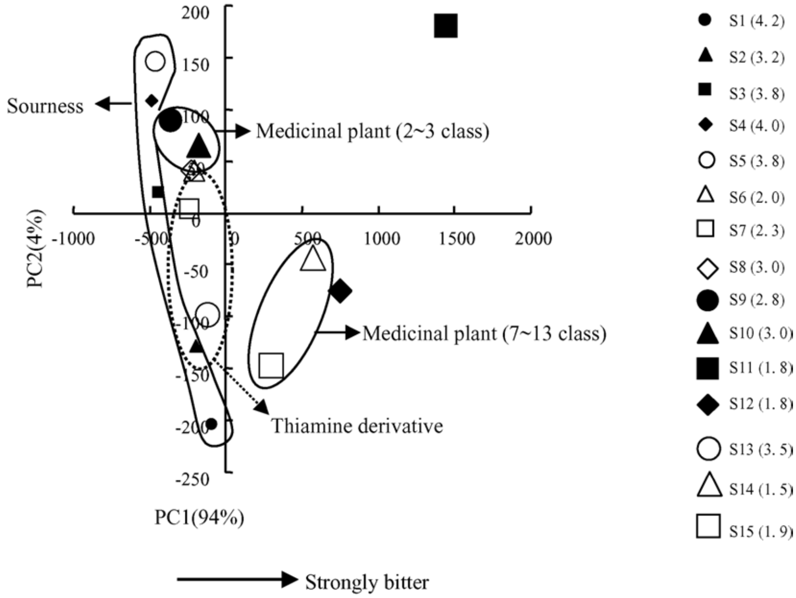

Fig. 5. Principal component analysis of taste sensor data from commercially available bottled nutritive drinks. The relative contributions of PC1 and PC2 were calculated to be 94 and 4%, respectively. Numbers in parentheses are the corresponding palatability scores. For further explanation, see text.

3.5. Principal component (PC) analysis of taste sensor and nose sensor data

A principal component analysis was performed on the data obtained from the taste sensor and/or the nose sensor for the 15 bottled nutritive drinks.

Firstly, PC analysis was used to estimate the largest and second largest relative contribution factors (PC1 and PC2) using the taste sensor data. The results are shown in Fig. 5. The relative contributions of PC1 and PC2 are 94 and 4%, respectively. PC1 can be assumed to represent the intensity of bitterness. By PC analysis of the taste sensor data, the drinks could be divided into four groups: group 1, drinks with high scores for sourness (five products); group 2, drinks containing two or three medicinal plants (two products); group 3, drinks containing thiamine derivatives (five products); and group 4, drinks containing 7–13 kinds of medicinal plants (two products). The overall palatability scores from human gustatory tests for these different groups were as follows: group 1, 3.8; group 2, 2.9; group 3, 2.8; and group 4, 1.7. This shows that the taste sensor was capable of predicting the overall palatability of the bottled nutritive drinks.

Secondly, we used PC analysis to estimate the largest and second largest relative contribution factors (PC1 and PC2) using nose sensor data. The results are shown in Fig. 6. The relative contributions of PC1 and PC2 are 99 and 1%, respectively. The factor PC1 can be assumed to represent the intensity of ‘tasting of a medicinal plant’. By PC analysis of nose sensor data, the nutritive drinks could be classified into four groups: a predominantly fruity group (eight products); drinks with a menthol smell (one product); drinks containing two or three medicinal plants (2 products); and drinks containing 7–13 kinds of medicinal plants (2 products). This supports our assumption that PC1 most closely reflects the item “tasting of a medicinal plant”, while PC2 seems to be a combination of two factors, the odor of fruit and menthol.

The overall palatability scores (from human testing) of the drinks in the four groupings made on the basis of the nose sensor data were as follows: drinks with a fruity flavor (score 3.4); drinks containing two or three medicinal plants (score 2.9); drinks with a menthol flavor (score 1.8); and drinks containing 5–13 medicinal plants (score 1.7). This demonstrates that the odor could be predicted comparatively easily by the nose

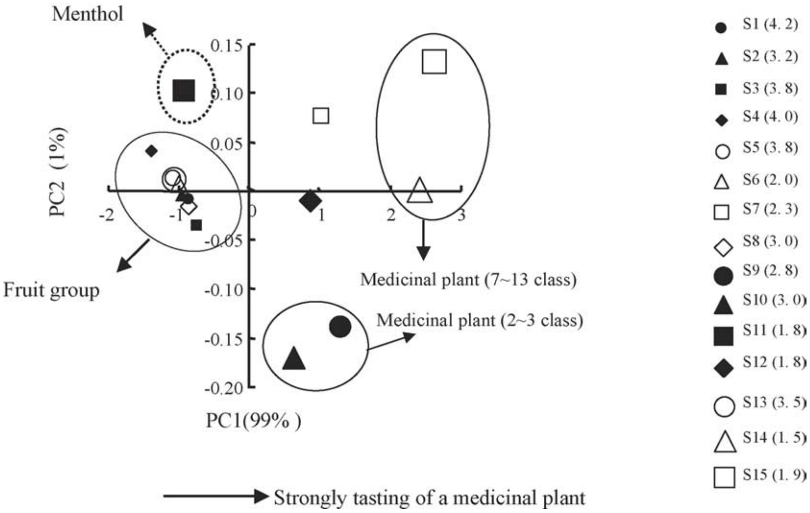

Fig. 6. Principal component analysis of nose sensor data from commercially available bottled nutritive drinks. The relative contributions of PC1 and PC2 were calculated to be 99 and 1%, respectively. Numbers in parentheses are the corresponding palatability scores. For further explanation, see text.

sensor, and shows the relation to overall palatability. The products S7 and S12 (containing thiamine and capsaicin, respectively) did not belong to any group. This is probably due to low sensitivity of the probe of the nose sensor to thiamine derivatives, and to capsaicin.

Thirdly, we used PC analysis to estimate the two largest relative contribution factors (PC1 and PC2) using a combination of taste and nose sensor data. The results are shown in Fig. 7. The relative contributions of PC1 and PC2 are 75 and 9%, respectively. Factor PC1

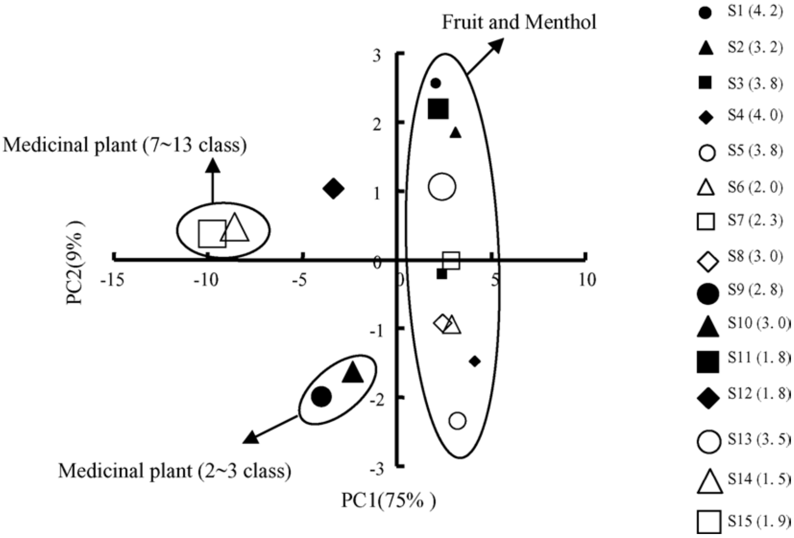

Fig. 7. Principal component analysis of taste and nose sensor data from commercially available bottled nutritive drinks. The relative contributions of PC1 and PC2 were calculated to be 75 and 9%, respectively. Numbers in parentheses are the corresponding palatability scores. For further explanation, see text.

can be assumed to represent the intensity of “tasting of a medicinal plant”, while PC2 seems to be a combination of two factors, odors of fruit and menthol flavors. By PC analysis of the combined data, the drinks were divided into three groups: a group containing fruity and menthol flavors (10 products); a group containing two or three kinds of medicinal plants (two products); and a group containing 7–13 kinds of medicinal plants (two products). The overall palatability scores obtained from human gustatory tests for these three groups were 3.2, 2.9, and 1.7, respectively.

PC analysis using a combination of nose and taste sensor data, resembles the analysis of the nose sensor data more closely than that of the taste sensor data. S12, the product for tired eyes and stiff shoulders, which contains not only medicinal plants but also the hot spice capsaicin, was not included in any group. S7 was included in the fruity and menthol group.

In this study the combined usage of taste and nose sensor data, while satisfactory, did not offer major advantages. A fruity flavor was positively correlated with palatability while ‘tasting of medicinal plants’ was negatively correlated. The optimization of taste and odor are critical factors in determining the overall palatability of drinks.

To our knowledge, the combined usage of taste and nose sensor has not been performed in related to medicines and related substances. Even though we did not have significant merit in the present study, further examination must find the advantages for this method.

4. Conclusions

The taste of 15 bottled nutritive drinks was evaluated by gustatory sensation results for various components of palatability and for the intensity of four basic tastes. The overall palatability was shown to be positively correlated with sourness and fruitiness ($R = 0.82$, and 0.86, respectively), and negatively correlated with bitterness and tasting of a medicinal plant ($R = -0.85$, and -0.80, respectively).

A high correlation was found between the taste intensity values obtained in human gustatory sensation tests and the predicted intensity scores for sourness and bitterness predicted by the taste sensor ($R = -0.92$, and 0.72, respectively). Moreover, a high correlation was found between overall palatability scores obtained in human gustatory tests and the intensity scores for fruitiness and tasting of a medicinal plant predicted by the nose sensor ($R = 0.73$, and 0.86, respectively).

By performing PC analysis on the taste sensor data, the drinks could be classified into four groups, with the ‘sour’ group showing the highest palatability score (3.8). By PC analysis using the nose sensor data, the drinks could be classified into four groups, with the ‘fruity’ group showing the highest palatability score (3.4). The products containing 7–13 kinds of medicinal plants showed the lowest palatabilities in both the taste and the nose sensor analysis. Finally, the combined use of taste and nose sensor seems to offer the potential for more precise evaluation of palatability.

Acknowledgements

This work was supported by a grant-in-aid from the Ministry of Education, Science, Sports, Culture and Technology of Japan Nos. 17590140 and 17790043.

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