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Artificial senses for characterization of food quality

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Abstract

Food quality is of primary concern in the food industry and to the consumer. Systems that mimic human senses have been developed and applied to the characterization of food quality. The five primary senses are: vision, hearing, smell, taste and touch. In the characterization of food quality, people assess the samples sensorially and differentiate "good" from "bad" on a continuum. However, the human sensory system is subjective, with mental and physical inconsistencies, and needs time to work. Artificial senses such as machine vision, the electronic ear, electronic nose, electronic tongue, artificial mouth and even artificial the head have been developed that mimic the human senses. These artificial senses are coordinated individually or collectively by a pattern recognition technique, typically artificial neural networks, which have been developed based on studies of the mechanism of the human brain. Such a structure has been used to formulate methods for rapid characterization of food quality. This research presents and discusses individual artificial sensing systems. With the concept of multi-sensor data fusion these sensor systems can work collectively in some way. Two such fused systems, artificial mouth and artificial head, are described and discussed. It indicates that each of the individual systems has their own artificially sensing ability to differentiate food samples. It further indicates that with a more complete mimic of human intelligence the fused systems are more powerful than the individual systems in differentiation of food samples.

Keywords: food quality, artificial senses, quality quantification, artificial neural networks, feature extraction, multi-sensor data fusion

1 Introduction

There are five primary senses: vision, hearing, smell, taste and touch. They are the functions of eyes, ears, nose, tongue and skin respectively. These functions are coordinated by the brain. In the characterization of foods people sense the samples and differentiate "good" from "bad" along a continuum. However, the human sensory system is l subjective, with mental and physical inconsistencies, and time consuming. Artificial senses such as machine vision, the electronic ear, electronic nose, electronic tongue, artificial mouth and even the artificial head have been developed which mimic human senses. These artificial senses are coordinated individually or collectively by a pattern recognition technique, typically artificial neural networks, which were constructed based on studies of the human brain. Such a structure is used to develop methods for the rapid characterization of foods. These methods are objective, computerized and typically non intrusive and non invasive.

Food quality is very important in product processing and consumption since it is an index which measures the competitiveness of products in the market. The key for artificial senses to characterize and to evaluate food quality is to quantify the quality of foods. The quality of foods is of primary concern both to the food industry and to the consumers. Consumers need quality foods to be tasteful, nutritious, and safe. Therefore, evaluation of the quality of foods is highly important to food manufacturers, distributors, sellers, and consumers.

In general there are two types of methods for evaluation of food quality. Subjective methods are based on the human assessment of the qualitative and quantitative values of the characteristics of the food. These methods usually involve perception of texture, flavor, odor, color, and touch. However, even though human evaluators are highly trained, their opinions vary because

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of mental and physical variability.

With computer and electronic technologies, fast and consistent signal measurement, data collection, and information processing and analysis become possible. Computerized food quality evaluation systems can consistently perceive deviation from standards. Such computerized systems can be built to mimic human senses but with none of the mental and physical problems of human evaluators. A digital camera can be connected to a computer equipped with image processing software to set up a machine vision system. An acoustic sensor can function as an electronic ear. An array of gas sensors combined with pattern recognition algorithms comprises an electronic nose. An array of electrochemical electrodes combined with pattern recognition algorithms can be an electronic tongue. These systems can function individually or in combination by multi-sensor data fusion which improve individual performance. By combining information from auditory, tactile and olfactory senses an artificial mouth can be built [1,2]. An artificial head is feasible if all five human senses are mimicked and combined[3]. This review will present and discuss the principles, structures, and applications of individual artificial sensing systems. With the concept of multi-sensor data fusion these sensor systems can work collectively to construct more powerful artificial sensing systems. Two such systems, the artificial mouth and the artificial head, will be described and discussed.

2 Basic methods

2.1 Food quality quantization

Food quality quantification is fundamental to artificial evaluation. It allows the relationships to be represented mathematically. With the procedure or the mathematical relationship the evaluation of food quality can be automated according to the logic of artificial senses. The concept is to mimic human senses with artificial senses which can “see”, “listen”, “smell”, “taste”, “touch”, and even “eat” the food and then differentiate the samples, typically with artificial neural networks often guided by results from a human sensory panel. Performance is usually measured by comparison of the quantitative data with sensory, classification assignment, and/or mechanical and chemical attributes [4]. In general, the procedure is as follows (Fig.1) [4]:

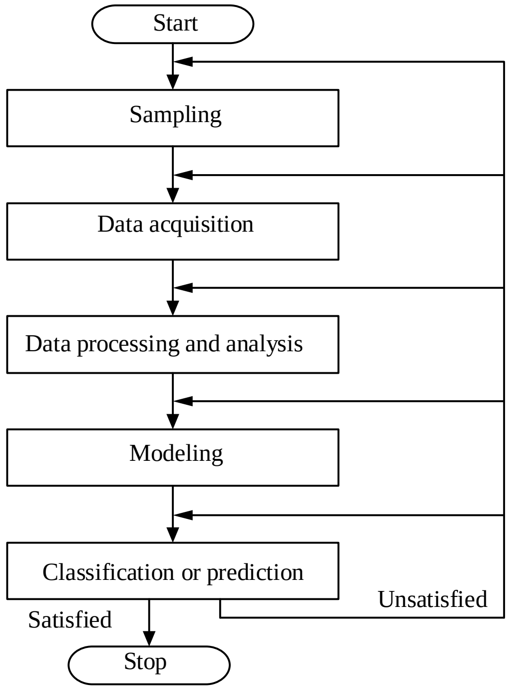

Fig.1 Diagram of the procedure for food quality quantization [4]

(1) Sampling procedure is designed to produce enough data for a conclusion to be drawn with adequate statistical significance. When the food samples are extracted, they usually need to be further processed, stored, and delivered to the experimental station for measurement.

(2) Sensors and transducers measure physical properties of the food samples. The data are conditioned, converted, and stored for processing and analysis.

(3) The data are processed, usually scaled or normalized, to produce a consistent magnitude amongst the variables. The relationships between variables are tested and the correlations between variables are determined. This step helps make decisions on modeling strategy.

(4) Empirical mathematical models are statistically built to produce quantitative relations between input(s) (physical properties) and output(s) (human sensory quantities, classification assignments, and/or mechanical and chemical measurements of the samples). A number of methods are available for building the models, such as discriminant analysis, Bayesian decision, statistical regression, etc.. Artificial neural networks provide a way of

organizing synthetic neurons to solve complex problems in a manner similar to the human brain. They are effective in capturing complex relationships between inputs and outputs in artificial sense-based food quality quantification [4].

(5) The food samples can be classified for their sensory, mechanical, and chemical attributes. The accuracy of the quantification is calculated to measure performance [5]. If the performance is good, the quantification scheme can be used in quality evaluation; otherwise, it may be necessary to reassess modeling, data processing and analysis, data acquisition, and/or the sampling procedure to decide where to refine the scheme.

2.2 Artificial neural networks

Neural networks have been used to solve complex problems such as pattern recognition, fast information processing and adaptation. The architecture of an artificial neural network (ANN) is a simplified version of the structure of the human brain. For problem solving, the human brain uses a web of interconnected processing units called neurons to process information. The vast processing power of biological neural structures has inspired their study as a model for man made computing structures. Pioneer studies [6–11] were conducted on the theory of artificial neural networks. In 1986, the Parallel Distributed Processing (PDP) group published results and algorithms [12, 13] about back propagation training of multilayer feed forward networks. This work gave a strong impetus to the area and provided the catalyst for much of the subsequent research and application of artificial neural networks.

A neural network is typically implemented by performing independent computations in some of the units and by passing the computed results to other units. Each of the processing units performs its computation based on a weighted sum of its inputs. In a network, the input units are grouped as the input layer and the output units are grouped as the output layer. Other units are grouped into hidden layers between the input and the output layers. An activation function is usually used to determine the output of each unit in the hidden and output layers. The connections between processing units, like synapses between neurons, are modified by weighting functions.

Artificial neural networks are used in mathematical modeling to establish the map between system inputs and outputs. They are especially useful in classical statistical modeling, which is based on linear model structure and parameter estimation. However, it is not necessary for ANN to know how the inputs and outputs are related. They always establish a relationship between system input and output as long as they are related in some way. So, artificial neural networks are important where a classical statistical model does not work well.

Fig.2 shows a typical fully connected multilayer

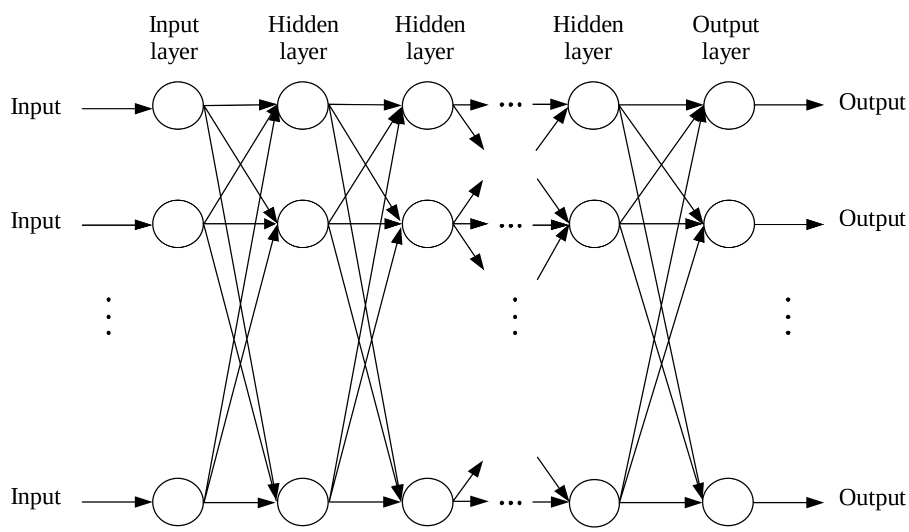

Fig. 2 Structure of a typical fully connected multilayer feed forward neural network[4]

feed forward neural network. This kind of neural network, especially with one hidden layer, is popular in solving problems in food science particularly in food quality quantification. Artificial sensing systems use ANN to take the array of sensor outputs as the network input by feature extraction and to generate the outputs as the indicator of sample classification or attribute values. Artificial neural networks analyze and differentiate what the sensors "see","hear", "smell", "taste", and "touch". Fig.3 is the general structure of an artificial sensing system.

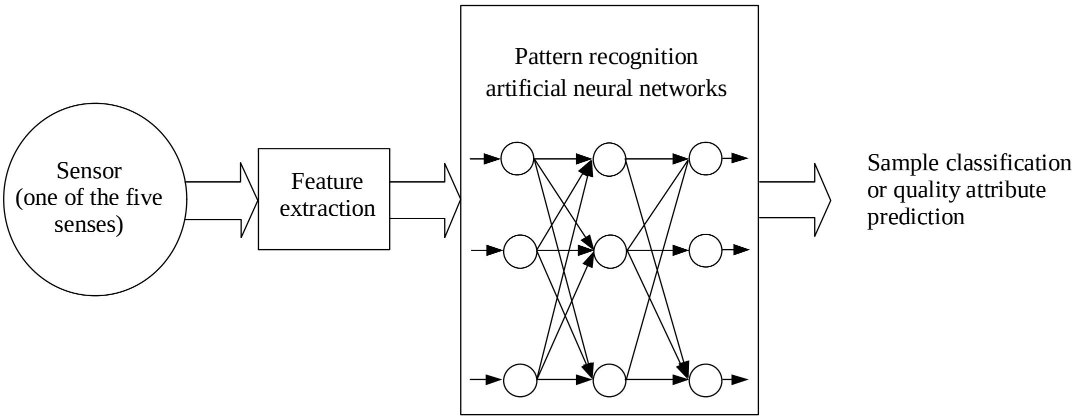

Fig. 3 General structure of an artificial sensing system

3 Machine vision

In a generic machine vision system (Fig.4) the most common imaging sensor is a digital camera connected to a computer. In recent years more exotic imaging methods have been used, many of which originate from medical profession. Dual energy X-ray [14], ultrasonic B-mode [15] and elastography [16], Magnetic Resonance Imaging (MRI) [17,18], and Computed Axial Tomography (CAT) [19] are a few examples.

A machine vision system has been developed at Texas A&M University for quantification of snack food quality [20]. A color digital camera captured images of a snack product. The image was processed, then texture, size, and shape features were used as input to an artificial neural network to predict sensory attributes of the snack which could then be used to describe the quality from a texture (mouth feel) standpoint.

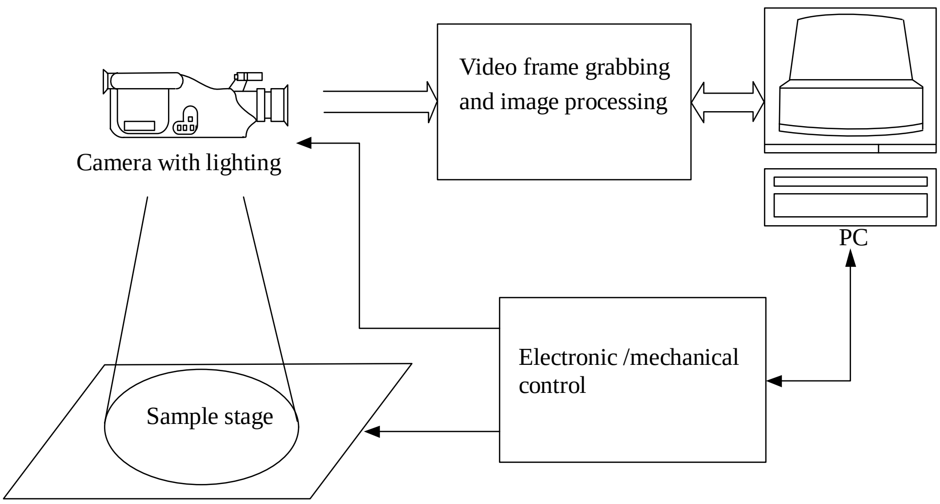

Fig. 4 Structure of generic machine vision system[4]

The image acquisition system (Fig.5) was equipped with a charged coupled (CCD) color camera that captured multiple frames (32 images per acquisition) of 512×512 pixels.32 frames were digitized per sample, and these samples were averaged to reduce noise. 50 images were acquired for each cell referred as different process conditions for each of the machine wear/raw material scenarios. One wear/raw material (see below) scenario had 16 cells giving 800 (16×50) images. The resolution was 0.183 mm per pixel. This experiment used the cross-sectional images of a typical puffed extruded corn product (Fig.6).

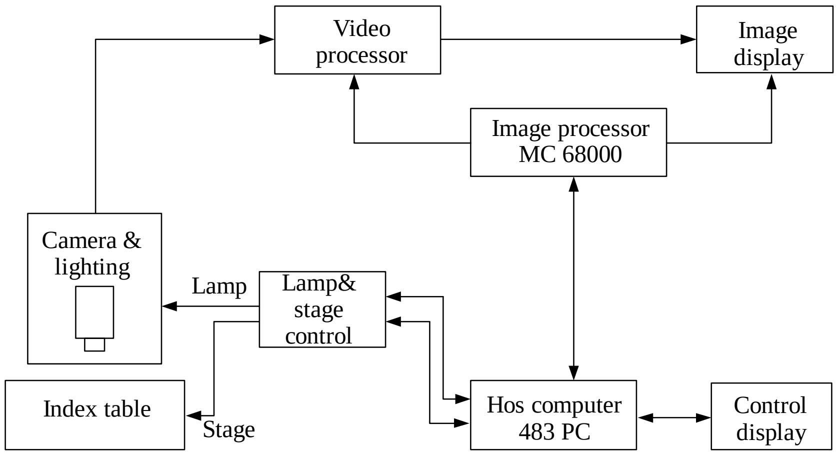

Fig. 5 Schematic diagram of the imaging system for snack food quality quantification [20]

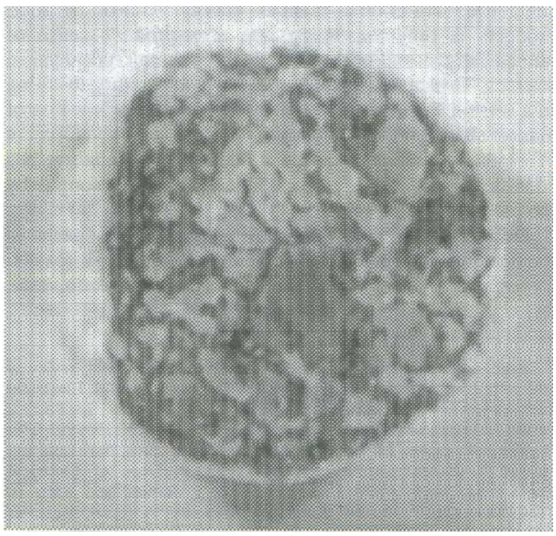

Fig. 6 Cross-section image of a typical snack product [20]

To obtain the morphological features, the images were thresholded based on their density histograms. The resulting binary images were then processed by a closing morphology operation with a disk structuring element to obtain size and shape of the snack products[21] which were described using the following nine features:

(1) Area (AREA) is the number of pixels contained in a snack object image; this number is converted into a physical size using the calibration parameter of the camera.

(2) Perimeter (PERIM) is the number of pixels along the boundary of a snack object image; the calibration parameter is used to compute the corresponding physical length.

(3) Fiber length (FIBERL) and width (FIBERW) are the length and width of a rectangle respectively surrounding a snack object image.

(4) Chord length (CHORDL) and breadth (CHORDB) are the longest chord and the shortest chord respectively passing through a snack object.

(5) Roundness (ROUND) is a shape factor, which has a minimum value of 1.0 for a circular shape snack. Large values of roundness indicate thinner and longer snacks.

(6) Fullness ratio (FULLR) is the ratio of the snack image area to the circumscribed area.

(7) Aspect ratio (ASPR) is the ratio of the length to the breadth of a snack object.

Thirteen textural features [22] were calculated based on co-occurrence matrices reflecting the spatial distribution of intensity variations from the images of the snacks:

1) Angular second moment (F_1).

2) Contrast (F_2).

3) Correlation (F_3).

4) Variance (F_4).

5) Inverse difference moment (F_5).

6) Sum average (F_6).

7) Sum variance (F_7).

8) Sum entropy (F_8).

9) Entropy (F_9).

10) Difference variance (F_{10}).

11) Difference entropy (F_{11}).

12) Formation measure of correlation number 1 (F_{12}).

13) Information measure of correlation number 2 (F_{13}).

In this way a total of 22 features,9 morphological and 13 textural, from snack images were extracted as the input parameters of the quality quantification to correlate with 7 sensory attributes as the output parameters that define the visual quality of the snack products established by the taste panel: ①bubble ②roughness ③cell size ④ firmness ⑤crispiness ⑥tooth packing ⑦grittiness of mass.

The taste panel scaled these sensory attributes in the range of 3 to 3 with 0 indicating the optimum value.

A one-hidden-layer neural network trained with a back-propagation algorithm modeled the relationship between the textural and morphological features and sensory attributes. The size of the network input layer is equal to the size of the feature vector, i.e. 22. The size of the output layer is the size of the sensory attribute vector, i.e. 7. The size of the hidden layer is determined by experiment. The number of the hidden nodes was incremented by 1 starting from 1 until the mean square error reached 0.1%. Thus the optimum number of hidden nodes was 9.Therefore; a 22×9×7 network was structured. The input values were normalized between 0 and 1.The output values, the taste panel grading from –3 to 3, were also normalized between 0 and 1.

The conditions of the machine and the raw material are important in the formation of the snacks. With the preset conditions, the sample data were used to model the relationship between the image features and sensory attributes. The input textural and morphological features were divided into four machine wear/raw material categories (A, B, C, and D). A total of 50 sample data vectors per cell constituted the training and validation data sets for neural network classification (Table 1).

Table 1 Training and validation sample data sets for different experimental setups [20]

Machine wear /raw material conditions	Number of training samples	Number of validation samples
A	700	100
B	400	50
C	400	50
D	400	100

The performance of the back-propagation trained neural network was evaluated by defining a classification rate:

$$\text{Classification rate }\% = \frac{NC}{N} \times 100 \tag{1}$$

where NC is the number of correctly classified samples, and N is the number of total samples.

The classification rates (Tables 2 and 3) are very high on training data and acceptably good on validation data. Thus the combination of textural and morphological image features is effective in quantifying the sensory attributes of snack quality with high accuracy from the neural network model when compared with human experts.

Table 2 Performance (% classification rate) of neural network on training data [20]

Machine wear/raw material conditions	Quality/sensory attributes						
	Bubble	Rough	Cell	Firm	Crisp	Tooth	Grit
A	96	98	90	94	93	94	97
B	91	91	98	97	96	89	93
C	95	95	94	88	92	91	97
D	99	100	96	96	99	97	98

Table 3 Performance (% classification rate) of neural network on validation data [20]

Machine wear/raw material conditions	Quality/sensory attributes						
	Bubble	Rough	Cell	Firm	Crisp	Tooth	Grit
A	92	90	83	88	85	84	94
B	90	98	98	98	94	94	92
C	90	94	86	78	82	82	90
D	90	93	78	95	87	88	90

4 Electronic nose

The olfactory anatomy of humans (Fig.7) can be simplified (Fig.8, Table 4 in detail). The receptor cells and cilia are replaced with nonspecific gas sensors that react to various volatile compounds. The transduction of the olfactory receptors is replaced with signal conditioning circuits that involve a conversion to voltage. Coding of the neural signals for intensity and recognition of odor in humans is replaced by a pattern recognition method, typically an artificial neural network.

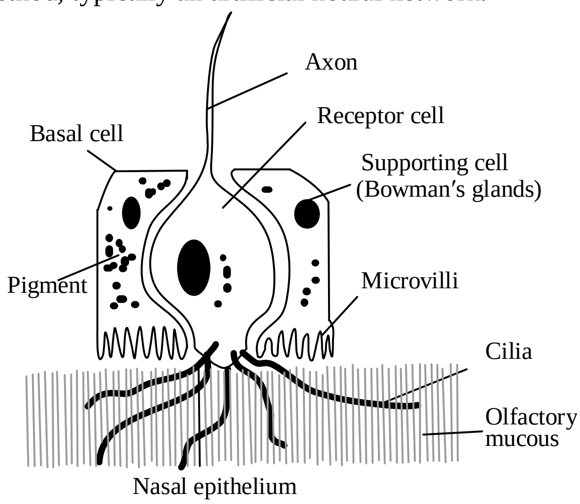

Fig. 7 Schematic of human olfactory organ [37]

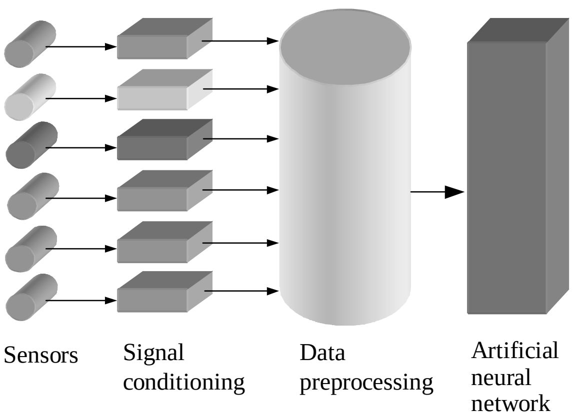

Fig. 8 Schematic of generic electronic nose[37]

Table 4 Comparison of human nose and electronic nose[37]

Item	Human nose	Electronic nose
Number of olfactory receptor cells/sensors	40 million	4 to 32
Area of olfactory mucosa/sensors	5 cm^2	1 cm^2
Diameter of olfactory receptor cell/sensor	40–50 micron	800 micron
Number of cilia per olfactory receptor cell	10–3	0
Length of cilia on olfactory receptor cell	100–150 micron	N/A
Concentration for detection threshold of musk	0.000 04 mg/literre	Unknown

Because there is generally no mucus into which the odorants dissolve, the molecules must adsorb onto the sensor. A variety of sensors have been employed based on metal oxides [23–26], semiconducting polymers [27–30], optical methods [31, 32], and quartz resonance [33–35]. Metal oxide and semiconducting polymer sensors are the two most commonly used sensors in commercial instruments.

An electronic nose can be used to characterize foods [36–44]. Osborn and Lacey at Texas A&M University developed a commercial electronic nose for detecting off flavors due to high temperature curing in peanuts [38, 45]. Peanuts were tested in four states of destruction: whole pods, whole kernels with red skins, half kernels without red skins, and ground kernels. Off-flavors in ground kernels were also measured using gas chromatography (GC) and an organic volatile meter (OVM) for comparison with the electronic nose. The electronic nose sensor array was able to distinguish off flavored peanuts after some data processing to remove bias. Further, the electronic nose was able to differentiate between the samples suggesting this technique could be used for quality control.

Fig.9 shows the response of a commercial electronic nose (Neotronics, Flowery Branch, GA, USA) to water vapor pressure for a series of ground peanut samples. The samples were at the same moisture content, and vapor pressure effects were caused by the absorption kinetics of the sensors. Fig. 10 shows a sample of the data collected from a single sensor in the AromaScan electronic nose on the low temerature cured ground kernels for all 10 test replications. Fig.11 is the data from the same sensor for the ground kernels cured at high temperature. Note that the low temperature readings appear to be generally constant with time, while the high temperature readings appear to increase as the test progresses.

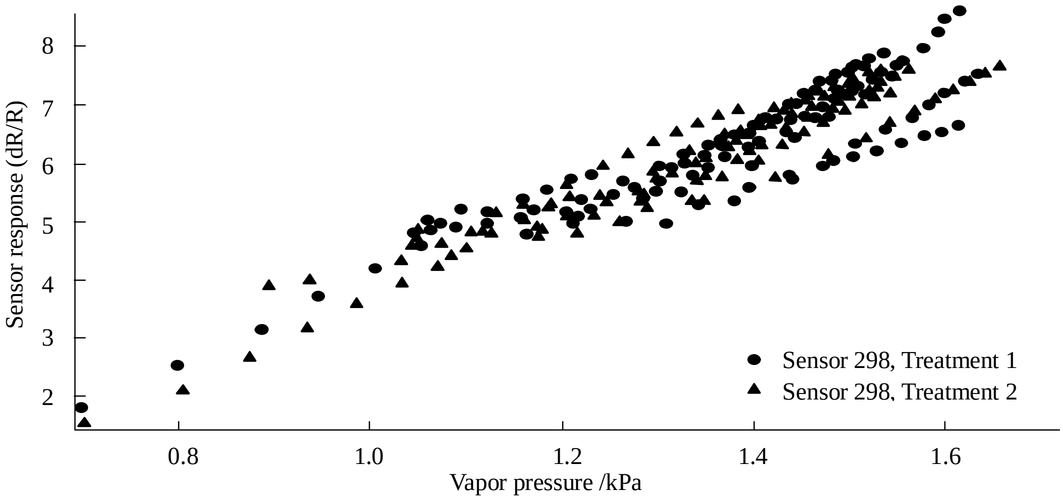

Fig.9 Response of a single sensor in the Neotronics electronic nose to vapor pressure for ground peanut samples [37]

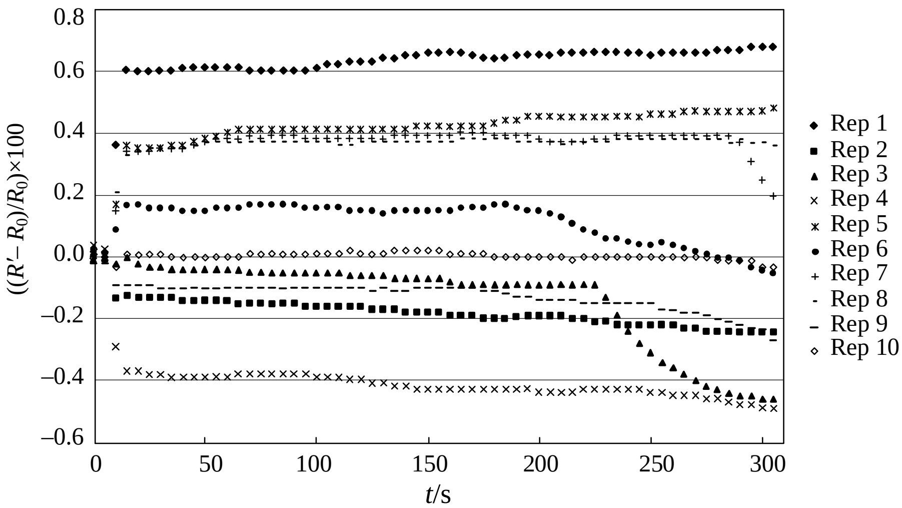

Fig.10 Raw AromaScan data from sensor 11, ground kernels, low temperature curing treatment for 10 replications [45]

Fig.12 shows all replications averaged for all 32 sensors of the AromaScan electronic noseand shows separation between treatments. T-values were calculated to compare the data sets combining all sensor data from the room-temperature and the high- temperature treatments with the electronic nose compared with GC and OVM (Table 5). GC and OVM methods have relatively low t-values compared to the electronic nose because of the variance between replications for the GC and OVM methods, the inherent error in these sampling techniques, and the large number of "internal replications" that can be obtained from the electronic nose using parallel sensors for a single test.

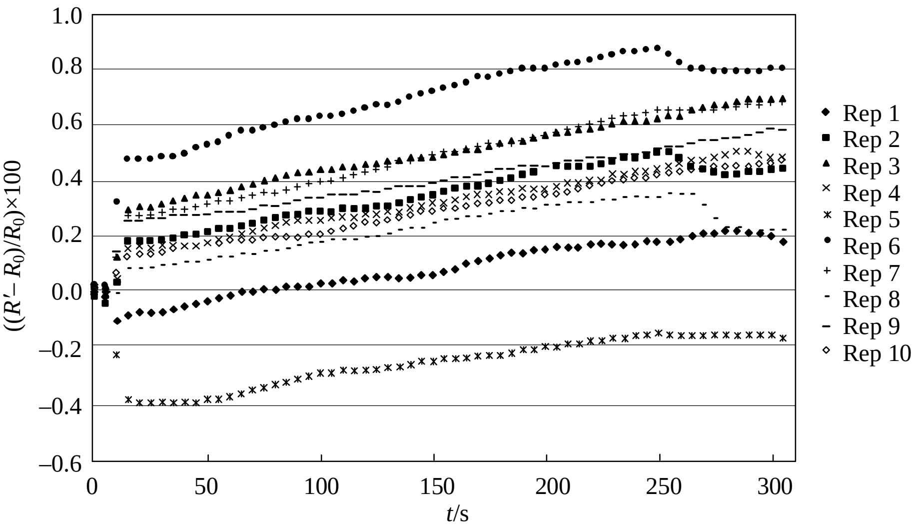

Fig.11 Raw AromaScan data from sensor 11, ground kernels, high temperature curing treatment for 10 replications[45]

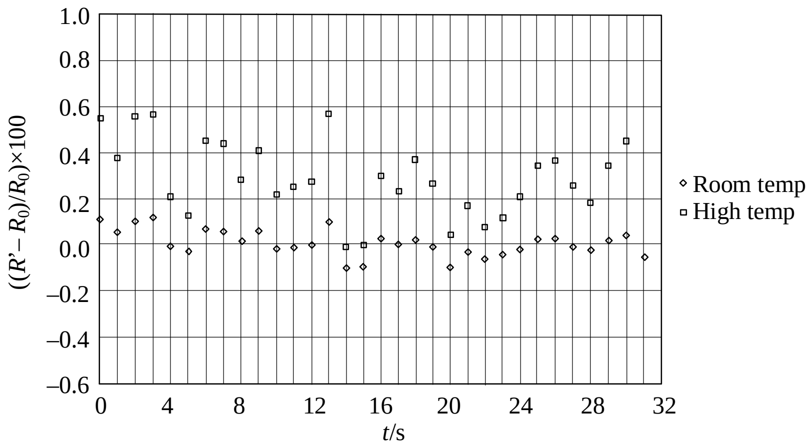

Fig.12 Graphic representation of all replications averaged for all 32 sensors of the AromaScan electronic nose [45]

Table 5 Calculated t-values for electronic nose and for GC and OVM for detecting off flavor volatiles in ground kernels [45]

Detection method	Replications (room/high)	t-value
Electronic nose, ground kernels (20 sensors, 210 s sampling time)	3/3	22.88***
Electronic nose, ground kernels (20 sensors, 60 s sampling time)	3/3	14.66***
GC ethanol	3/3	3.76**
GC acetaldehyde	3/3	11.4***
GC ethyl acetate	3/3	2.52*
OVM	3/4	3.59**

*Significant at 0.1 level. **Significant at 0.05 level. *

Artificial neural networks are powerful at coding the sensor response although the t-test method was effective. Artificial neural networks model the following nonlinear relationship between sensor readings and sample classification assignment:

Artificial neural networks are powerful at coding the sensor response although the t test method was effective. Artificial neural networks model the following nonlinear relationship between sensor readings and sample classification assignment:

$$\hat{C} = \hat{f}\left(x_1, x_2, \cdots, x_n; \hat{\Theta}\right) \tag{2}$$

where $\hat{f}\left(x_1, x_2, \cdots, x_n; \hat{\Theta}\right)$ is the nonlinear function estimate, $\hat{\Theta}$ is the set of coefficient estimates, $x_i\left(i = 1,2,\cdots,n\right)$ is the ith sensor response, and n is the number of the sensors in the specific electronic nose, 12 for Neotronics and 32 for AromaScan.

The electronic nose must be trained by presenting it with known odors. When presented with an odor for which no training data exist, the electronic nose is unable to classify the sample. In this aspect, the electronic nose is similar to the human sense that is shaped through experience.

Determining the structure of a neural network is an empirical process and time consuming. A trained neural network can rapidly classify a new series of data for a particular odor.

5 Electronic tongue

Artificial taste systems have been developed [46–48] called "electronic tongue" or "taste sensor".

An electronic tongue can use optical methods or measurements of mass changes of vibrating quartz crystals. In an electronic tongue based on pulse electrochemical voltametry[3,48,49]. The measurement was carried out by a standard six-electrode configuration. The current transients due to onset of a voltage pulse can indicate both the amount and type of charged molecules and of redox active species. The six working electrodes were gold, iridium, palladium, platinum, rhenium and rhodium. There was also an auxiliary electrode and one reference electrode. The system was placed in a 150 ml measurement cell. The response was measured by a potentiostat connected to a PC via an A-to-D converter. Fig.13 shows a measurement sequence covering 11 cycles resulting in a final pulse value of –220 mV. The sequence starts with an applied potential of 800 mV for 0.5 s. The voltage is then set to 0, the applied potential is decreased by 100 mV, and the cycle starts again.

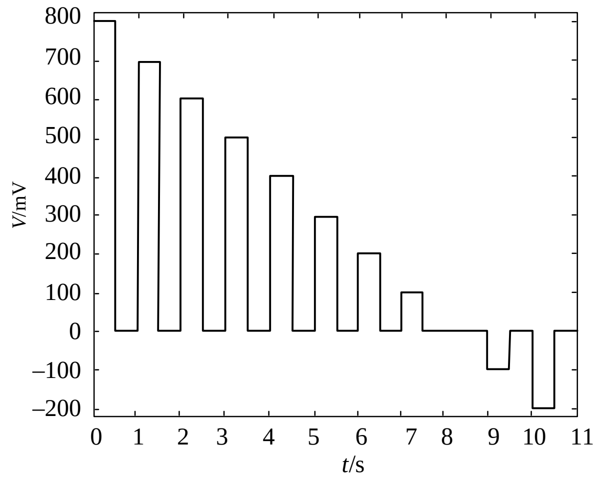

Fig.13 A measurement sequence of an electrode of an electronic tongue covering 11 cycles resulting in a final pulse value of –220mV[3]

Fig.14 shows a typical recording of a full measurement over all electrodes. The sample rate is set to 20 Hz and only the amplitude which has shown to contain sufficient information, namely from the first, second and last samples in each 0.5 s interval, was used in this experiment. Each electrode measurement is characterized by 66 samples; hence, a total tongue measurement comprises 396 samples.

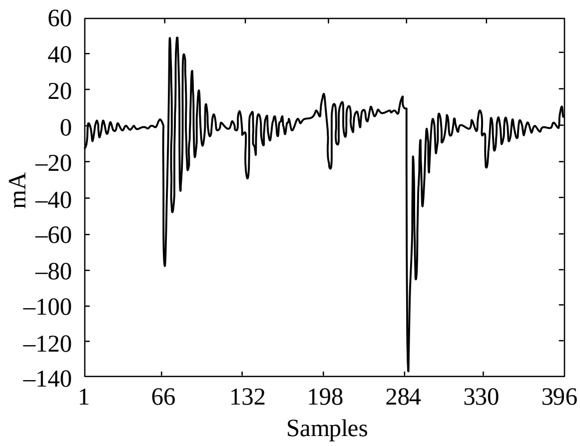

Fig.14 A typical recording of a full measurement over all electrodes of an electronic tongue[3]

Current transient responses obtained at different potentials can be analyzed using pattern recognition especially with artificial neural networks. The electronic tongue was able to distinguish liquids such as fruit juices, still drinks and to follow aging of milk [48, 50]. The electronic tongues are commercially available, such as Taste Sensing System SA401 of Anritsu Corp. (Japan) and the Astree Liquid and Taste Analyzer of Alfa MOS (France).

6 Multi-sensor data fusion

Multisensor data fusion is an emerging technology is used by department of defense for automated target recognition. Non-DoD applications include monitoring of complex machinery, robotics, environmental surveillance and monitoring, medical diagnosis, smart building and food quality [51–54]. Techniques for data fusion are drawn from a wide variety of disciplines, including signal processing, pattern recognition, statistical estimation, artificial intelligence, and control theory. The rapid evolution of computers, proliferation of micro-mechanical/electrical systems sensors, and the maturation of data fusion technology provide a basis for utilization of data fusion in everyday applications[55].

Multi-sensor data fusion provides an approach to improving the performance of single sensors. In general a single sensor system provides a limited measure of only a single aspect of an object. A machine vision system basically "views" the object to identify textural and morphological features[56]. An acoustic sensor "hears" the sound from the object. An electronic nose "smells" the object and differentiates one object from other with different gas sensor array signatures [57]. A taste sensor "tastes" the object and differentiates between objects with different taste sensor signatures [58–60]. A force sensor basically "touches" the object. If these sensors work together, the integrated or fused system should be able to "see", "hear", "smell", "taste", and/or "touch" the object and the decision about the object would be based on a compilation of what it sensed. This idea suggests developing a computerized sensing system which will act similarly to human appreciation of food with the combination or fusion of five senses.

Based on the measurement of each artificial sensor, the quantified features can be extracted from each sensor's output and combined as the following vector:

$$\boldsymbol{F} = [\ \boldsymbol{f}_1, \boldsymbol{f}_2, \cdots, \boldsymbol{f}_n\ ]^{\mathrm{T}} \quad (2 \leq n < 5) \tag{3}$$

where $\boldsymbol{f}_i$ is the feature vector from an individual artificial sensor, version, acoustic, gas, taste and/or force.

How to fuse the information depends on what sensor systems and information available. For example, if only the information of the gas sensor and taste sensor is available, the fusion can be as follows:

$$\boldsymbol{F} = [\ \boldsymbol{f}_{\mathrm{gas}}\ \ \boldsymbol{f}_{\mathrm{taste}}\ ]^{\mathrm{T}} \tag{4}$$

If the information of the acoustic sensor, the gas sensor and the force sensor is available, the fusion can be done as:

$$\boldsymbol{F} = [\ \boldsymbol{f}_{\mathrm{acoustic}}\ \ \boldsymbol{f}_{\mathrm{gas}}\ \ \boldsymbol{f}_{\mathrm{force}}\ ]^{\mathrm{T}} \tag{5}$$

This fusion is the foundation of artificial mouth, which will be described later. Fig.15 shows the structure of the data fusion with these three sensors. With the feature vector as the input, artificial neural networks are an appropriate approach to differentiate the data in which nonlinear relationships exist. The output of the network is a vector to contain binary values to associate it with one class. For example, two output nodes of the network can be used to discriminate the data between two classes. Each node is associated with one class. When the data belong to class I, the output vector $\boldsymbol{O}$ = $[1\ 0]^{\mathrm{T}}$ and when the data belong to class II, the output vector $\boldsymbol{O} = [0\ 1]^{\mathrm{T}}$. Integration of advanced statistics and artificial neural networks is another potential to analyze the fused data for this application referred to our previous successes in the integration of partial least square and artificial neural networks (NNPLS) and principal component analysis and artificial neural networks (NNPCA)[61].

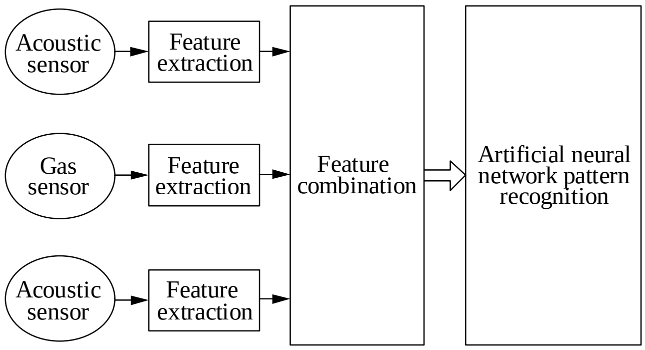

Fig.15 Structure of data fusion of three sensors: acoustic, gas and force

An artificial mouth[1,2] was built by combining information corresponding to three senses "auditory" by a microphone, "tactile" by a force sensor and " olfaction " by a gas sensor array.

A piston in a chamber containing a crisp food sample was moved at a constant speed by the action of a stepper motor connected to a lever. A force sensor recorded the force applied to the piston, and a microphone was placed at the bottom of the chamber. Gas samples from the chamber were led to a sensor array consisting of 10 MOSFET gas sensors, and four semiconducting metal oxide type sensors.

The chamber system was tested by estimating aging of, and classifying, different potato chips by collecting, analyzing and fusing crunching, hearing and smelling information[2]. The results indicated that information for touch, smell and sound was not sufficient to follow the aging process of the chips. But when the individual sets of information were merged, the aging process can be clearly followed by the pooled information.

An artificial neural network was able to predict aging. the nine most significant features, 3 chosen from each of sensing sources: smell, sound, and touch by principle component analysis, were fed into the network as the input. One output was the aging time. Seven nodes in the hidden layer were determined. The resulting prediction of aging time versus the true aging time is shown in Fig.16. Ideally, the prediction should follow the line.

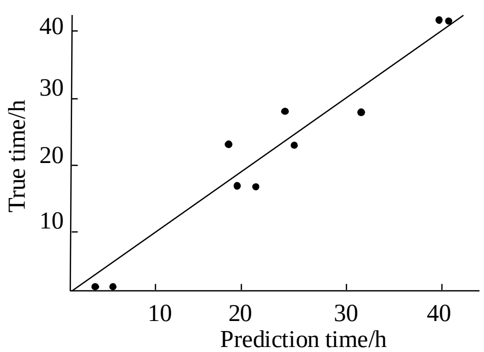

Fig.16 True versus predicted aging time [2]

Using the same method as for estimating aging time various potato chips were analyzed and classified satis-
f

An electronic sensor head is a mimic of all five human senses that makes a complete sensory evaluation of foods[3]. The food sample was placed into an artificial mouth to detect resistance to chewing, measure aroma and record the sound of chewing. A video camera was used to record color, shape and other properties of the sample. Finally, the crushed sample was mixed with a saline solution, and an electrochemical multi-electrode arrangement analyzed the mixture.

An artificial head combines the information from all five sensor systems: visual, acoustic, gaseous, gustatory, and force. Features can be extracted from the information from each sensor system and combined as the input for pattern recognition:

$$\boldsymbol{F} = [\ \boldsymbol{f}_{\text{vision}}\ \boldsymbol{f}_{\text{acoustic}}\ \boldsymbol{f}_{\text{gas}}\ \boldsymbol{f}_{\text{taste}}\ \boldsymbol{f}_{\text{force}}\ ]^{\mathrm{T}} \tag{6}$$

Artificial neural networks can thus be used to classify foods and to estimate quality parameters although a fuzzy classifier was suggested in the description.

This artificial head has been used for quality estimation of crisp products such as crisp bread and chips. The vision system alone could predict the freshness, spots and spiciness, the olfactory analogue the spiciness, and the auditory and touch analogues the freshness. Thus the freshness of the chips could be determined by change in color and by change in texture. Also, the spiciness of the chip could be determined by the smell and by the number and color of the spices as seen by the camera. Therefore, if all senses were fused together, all quality parameters could be predicted.

7 Conclusions

Artificial neural network pattern recognition and individual and fused sensor systems of artificial senses can quantify food quality. Machine vision and the electronic nose are the most successful methods. Electronic nose systems will be more effective with better understanding of the human olfactory system and with more powerful pattern recognition techniques by artificial neural networks. Compared with individual sensors, multi-sensor data fusion is relatively new in food quality quantification. The artificial head is still in a stage preliminary study. The approaches to multi-sensor data fusion are still under research. There are different levels of data fusion. Low level fusion adds signals from different sensors. High level fusion analyzes the features from individual sensor systems then associates them to produce a fused result. The best method to determine the level of fusion for different problems in food quality quantification is still to be determined.

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