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Development of mobile electronic nose for beef quality monitoring

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Abstract

Meat is one of foodstuff that widely consumed in the world. Unfortunately, the quality of meat can easily degrade if not handled properly and become the serious health hazards if consumed. Hence, the food safety system is very important to guarantee the quality of food to be consumed. In this study, we introduced the development of mobile electronic nose for beef quality detection and monitoring. This system is developed using low-cost hardware and possible to integrate with cooling box or refrigerator for real time monitoring and analysis during distribution and storage processes. K-Nearest Neighbor with signal preprocessing is used to classify two, three, and four classes of beef. The experimental results show that the system can perfectly distinguish fresh and spoiled beef. Moreover, it has promising classification accuracy for binary, three classes, and four classes classification with 93.64%, 86.00%, and 85.50%, respectively. Hence, this system has a potential solution to provide low-cost, easy to use, and real-time meat quality monitoring system.

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Keywords: Mobile Electronic Nose; Beef Quality Monitoring; Classification; K-Nearest Neighbor

1. Introduction

Meat is the main product of livestock as a source of protein for humans. The Food and Agriculture Organization of the United Nations has been reported that the per capita meat consumption in the developing countries is still continuously growth (about 1.3%) until 2050. Meanwhile, although meat consumption in developed countries has decreased, the meat consumption per capita is still high (the 80 kg at present). On the other side, meat is good media for microbial growth. Hence, it is easy to decay if not handled properly. The storage of meat in the open air can

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accelerate the meat quality degradation. For instance, the beef storage life is about 20 hours if exposed by open air [1] compared 10-12 weeks in the vacuum-packed storage [2]. In fact, many improper handling of meat in developing countries occurs. Meat left for hours exposed to air in the market. Moreover, the meat quality degradation also occurred during distribution processes. The biotic factors, ambient temperature, humidity, and transportation are causative factors of meat quality degradation [3]. The spoiled meat products consumption can trigger serious health hazards. So, it is very important to develop the mechanism to monitor and assess the quality of meat products.

Until now, the analysis of the total count of bacteria is the gold standard to determine the quality of meat products. However, the drawbacks of this approach are complicated, laborious, and needs more than 72 hours to get the analysis results [4]. It contrasts with requisites of the meat industry and the end consumers that need more rapid, simpler, and cheaper system for meat quality assessment and monitoring.

On the other hand, the development of machine olfactory system as known as electronic nose (e-nose) is a prospective instrument in many areas. Hitherto, food/product quality control is one of widely used of e-nose utilization. For instance, e-nose coupled with a pattern recognition algorithm has been successful to classify tea [5–10] and coffee [11,12]. It also uses to assess livestock products such as milk [13,14], beef [15–20], sex pheromones detection secreted by cows [21]. Furthermore, wireless e-nose also has been reported to detect the odors [22,23]. The advantages of e-nose utilization are cheap, easy to operate, and suitable for online monitoring and analysis [24]. In this paper, we introduce the development of mobile e-nose (MoLen) and the prospective applications in meat quality monitoring and detection. In this study, the cost of proposed device is only USD 300. It is cheaper when compared with Fourier Transform Infrared spectroscopy (USD 10000-35000) and gas chromatography (USD 3000-70000). More detail comparison of meat freshness evaluation techniques was explained by Wojnowski et al. [4].

The rests of paper has organized as follows: the first section gives a brief overview of the meat quality problems and potential of e-nose for meat quality assessment. The second section describes the e-nose development including the basic principle of e-nose, the proposed scheme of e-nose application, and the experimental setup in this study. The third section presented the results and discussion. Finally, the last section is the conclusion of this paper.

2. The development of mobile electronic nose

In this section, the basic principle of e-nose is explained and the proposed scheme of mobile electronic nose applications is demonstrated. Moreover, the materials and methods used are also discussed.

2.1. The basic principle of e-nose

E-nose is an instrument that mimics the mammalian olfactory system. The functional components of e-nose are similar with the mammalian olfactory system. Fig. 1 shows the functional components of e-nose compared with the component of mammalian olfactory system [25].

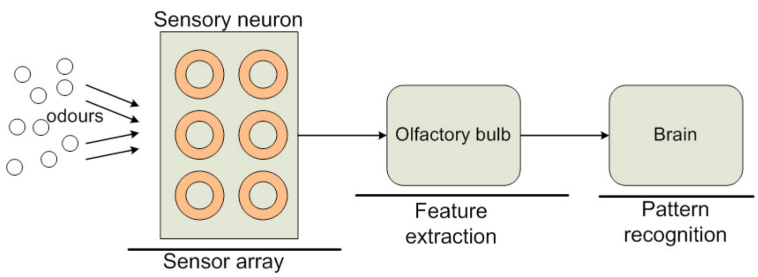

Fig. 1. The functional component of mammalian olfactory system and e-nose.

The volatile odor molecules are detected by sensory neuron. In a human olfactory system, there are about 100 million sensors which have different selectivity of various gases. In the e-nose system, sensor array acts as sensory neuron. The olfactory bulb extracts and transmits the signals to the brain. The pattern (a set of signals) is processed in the brain to recognize the pattern and produce the appropriate responses. The functions of olfactory bulb and pattern recognition are replaced by a computer which runs the particular feature extraction and pattern recognition algorithm.

2.2. The proposed scheme of mobile electronic nose application

In the development of e-nose for the beef quality monitoring system, the e-nose module is placed at the remote area and pattern recognition system is performed in the computer server. Fig. 2 demonstrates the implementation scheme of MoLen for beef quality monitoring.

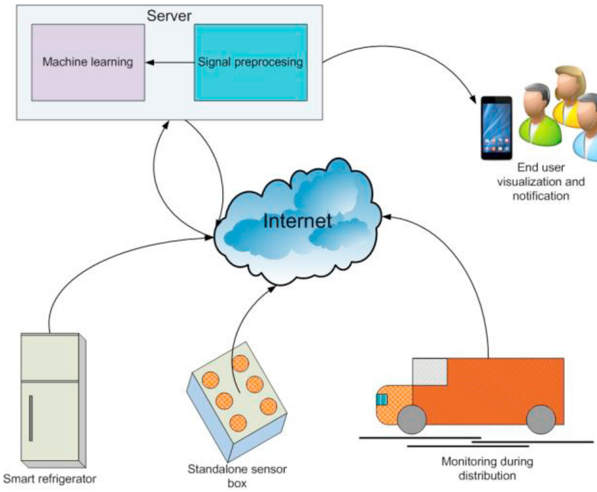

Fig. 2. The implementation scheme of mobile e-nose for beef quality monitoring

Besides in the form of standalone sensor box, MoLen can be integrated with smart refrigerator for meat quality monitoring and shelf-life prediction. The proposed system can also give the solution of monitoring during the meat distribution processes. The signals from all devices are transmitted via wifi/GSM networks to the main server. Finally, the end user is available to monitor the quality of beef using their computer or smartphone. Also, the system also can give notifications related to the beef quality status.

2.3. Materials and methods

In this study, sensor array consists of 10 gas sensors (MQ135, MQ136, MQ2, MQ3, MQ4, MQ5, MQ6, MQ7, MQ8, MQ9) + temperature and humidity sensor (DHT22). The combination of sensors in the initial sensor array is not optimal because of the high amount of overlapping selectivity between sensors. For instance, MQ2, MQ3, MQ4, and MQ9 have the same selectivity to detect methane. In this case, the sensor array optimization has to be performed to select the best sensor combination for beef quality monitoring. This process is necessary because the huge amount in sensor array with overlapping selectivity leads to waste of electrical energy, increase the size of transmitted data, and machine learning performance degradation because of redundant features. Hence, MQ2, MQ135, MQ6, DHT22, MQ4, MQ136, and MQ9 are used based on sensor array optimization result. The interested readers can see on our previous work about sensor array optimization[26]. The sensors are tailored based on Arduino platform. Arduino Mega SDK microcontroller is used as main board for all components. In addition, wifi-shield module is utilized for to transmit the data from the sensor array to server. Fig. 3 is the prototype of MoLen sensor box for beef quality detection.

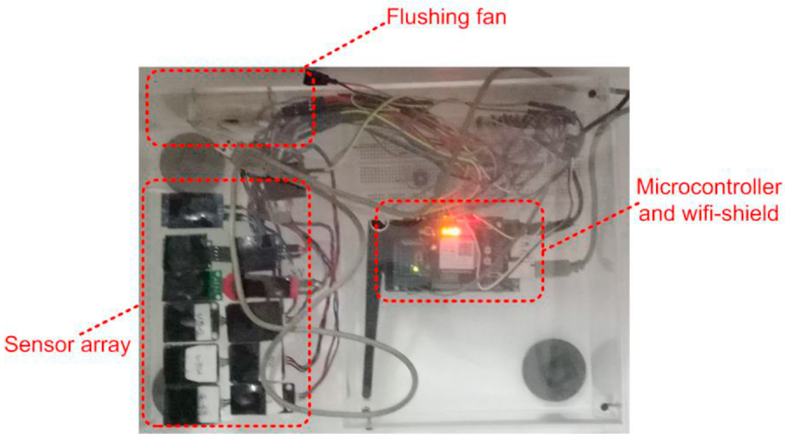

Fig. 3. The prototype of MoLen sensor box

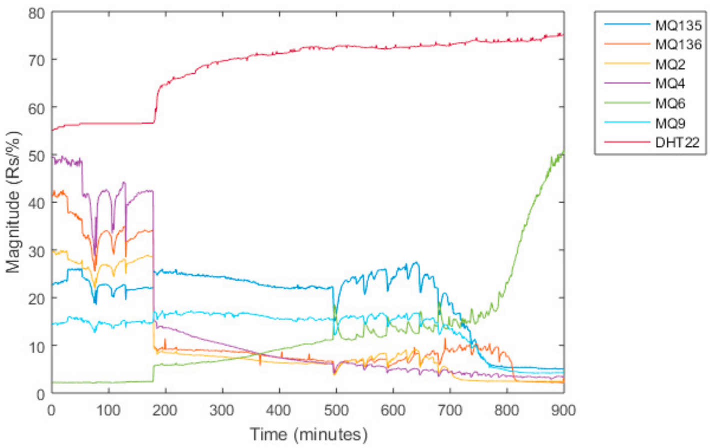

Fig. 4. E-nose signals during beef spoilage process

In this experiment, 500g of a beef placed in the sample chamber below the sensor array. The experiments performed at room temperature in an uncontrolled environment. The changes of gas concentration were observed until the beef sample decays. The multivariate responses from sensor array are transmitted to the server every minute. Based on this scenario, we can get more data for training and testing. The gas sensor resistance value (*Rs*) is obtained based on Analog to Digital Conversion (ADC) value from Arduino microcontroller as shown in (1).

$$Rs = \frac{Vc - V_{RL}}{V_{RL}} * RL \tag{1}$$

Where,

$$V_{RL} = \frac{ADC * Vc}{1023} \tag{2}$$

Vc, V_{RL}, *RL*, and *ADC* are a standard voltage of microcontroller (5V), actual voltage of sensor, sensor load resistance based on Ω meter, and analog to digital value, respectively. The signals are recorded during the process of beef spoilage. The multivariate data from sensor array is shown in Fig. 4.

The values of gas sensor resistance (*Rs*) are recorded and relative humidity values (%) from DHT22 are acquired. In this experiment, the implementation scheme in Fig. 2 was simulated by using local client server architecture. The sensor box acts as client which transmits data to PC as server for further analysis and visualization.

The sensory classes are divided into two, three, and four which is referred to standard issued by Meat Standards Committee of ARMCANZ (Agricultural and Resource Management Council of Australia and New Zealand)[2]. Actually, this standard distinguishes the beef quality into four classes but the most of the previous works divided the beef quality into two[17,20,27,28] and three classes[15,16,29,30]. Hence, we also consider regrouping the classes into two and three classes to investigate the performance. Table 1 explains the standard of beef quality.

Table 1. The beef quality sensory classes

Class	Microbial population ($\log_{10}$ cfu/g)
Excellent (E)	< 3
Good (G)	3-4
Acceptable (A)	4-5
Spoiled (S)	>5

*cfu/g: colony forming unit of bacteria in 1 gram of beef

Spectrophotometer and hemocytometer are used to count a number of bacteria (microbial population) for ground truth. In binary classification, the beef quality is distinguished into fresh and spoiled[17,20,27,28]. According to Table 1, binary classification is performed by grouping excellent, good, and acceptable classes into fresh class and the remaining for spoiled ($\{E,G,A\} \in fresh$ and $S \in spoiled$). Furthermore, three classes are divided into fresh, semi-fresh, and spoiled[15, 16, 29, 30]. This classification is obtained by grouping good and acceptable classes into semi-fresh class and the remaining classes are mapping into fresh and spoiled ($E \in fresh$, $\{G,A\} \in semi\text{-}fresh$, and $S \in spoiled$). Discrete Wavelet Transform (DWT) is utilized for signal preprocessing. The signals contaminated with noise is reconstructed by several mother wavelets which selected based on the Information Quality Ratio (IQR) values[1]. The magnitude differences between gas sensor responses have to be normalized to get the same scale. For this purpose, the feature scaling method for feature *a* can be mathematically computed in (3).

$$a' = \frac{a - \min(a)}{\max(a) - \min(a)} \tag{3}$$

In this preliminary study, we use instance-based learning such as k-Nearest Neighbors (k-NN) algorithm for classification. It is the simplest machine learning method but the performance of k-NN has been reported for the better result compare with support vector machine (SVM) and artificial neural network (ANN) to perform binary classification[20]. The distance between training (*v*) and testing (*w*) sample is measured by Euclidean distance (*D*) which expressed in (4).

$$D(v,w) = \sqrt{\sum_{i=1}^{n} (v_i - w_i)^2} \tag{4}$$

The class of testing sample (*class*) is determined by (5)

$$class = \arg\_\max_i \left\{ \frac{k_i}{k} \right\}, i = 1,\ldots,m \tag{5}$$

Where k_i, k, m are the number of neighbors for class *i,* the total number of nearest neighbors, and the number of class, respectively. In this study, the value of *k* is 5. In this study, we use MATLAB R2015a to process and visualize the sensor array data.

3. Results and discussion

Accuracy, precision, recall, and F-measure are used to measure the performance of classification. These values can be obtained according to (6)(7)(8)(9).

$$accuracy = \frac{\sum TP + \sum TN}{\sum total\_sample} \tag{6}$$

$$precision = \frac{\sum TP}{\sum predicted\_positive} \tag{7}$$

$$recall = \frac{\sum TP}{\sum label\_positive} \tag{8}$$

$$F-measure = 2 \times \frac{precision \times recall}{precision + recall} \tag{9}$$

Where, *TP, TN, total sample, predicted positive, label positive* are true positive, true negative, predicted condition positive, and condition positive based on class label, respectively. To generalize and prevent overfitting on the model, holdout cross validation is used. We get 1400 data and split 50% on each class. The data were randomly assigned into two set d_0 and d_1 for training and testing, alternately. Furthermore, the result of binary classification is demonstrated in Table 2. The prefix "t" and "p" imply true/actual and prediction, respectively. In binary classification, the average accuracy is 93.64%. Moreover, the average of precision and recall are 94.19% and 94.52%, respectively. This result indicates that k-NN can produce a satisfied performance to distinguish fresh and spoiled beef in beef quality monitoring. This result denotes that k-NN with proper signal preprocessing has a promising performance in binary classification of beef quality. Using the larger dataset, it is still comparable with the previous works[17, 20, 27, 28].

Table 2. Confusion matrix for binary classification

Data testing	Confusion matrix			Recall (%)	Precision (%)	F-measure (%)	Accuracy (%)
		p-fresh	p-spoiled				
d_0	t-fresh	385	0	100.00	100.00	100.00	100.00
	t-spoiled	0	315	100.00	100.00	100.00	
		p-fresh	p-spoiled				
d_1	t-fresh	294	0	100.00	76.76	86.85	87.29
	t-spoiled	89	317	78.08	100.00	87.69	
		Average		94.52	94.19	93.64	93.64

The more intricate case is three classes classification of beef quality. Table 3 demonstrates the three classes classification. Quite a lot of errors occur in semi-fresh prediction. It caused by not too much concentration difference of biomarkers such as H_2S, CO_2, and NH_3 in fresh and semi-fresh beef. The average accuracy, precision, and recall are 86%, 88.74%, 83.88%, respectively. The results indicate the proposed method can handle multiclass classification even though the performance should be improved. Using a larger dataset, it is also comparable with the previous works in three classes classification with 85% of accuracy using ensemble classifier [16] and 89% of accuracy using Support Vector Machine [15].

Table 3. Confusion matrix for three classes classification

Data testing		Confusion matrix			Recall (%)	Precision (%)	F-measure (%)	Accuracy (%)
		p-fresh	p-semifresh	p-spoiled				
d_0	t-fresh	36	107	0	25.17	100.00	40.22	84.71
	t-semifresh	0	242	0	100.00	69.34	81.90	
	t-spoiled	0	0	315	100.00	100.00	100.00	
		p-fresh	p-semifresh	p-spoiled				
d_1	t-fresh	142	0	0	100.00	100.00	100.00	87.29
	t-semifresh	0	152	0	100.00	63.07	77.35	
	t-spoiled	0	89	317	78.08	100.00	87.69	
		Average			83.88	88.74	81.19	86.00

Furthermore, Table 4 is the result of four classes classification. The success rate for excellent class detection is still low. In the other hand, the success rates of other classes are satisfied. The classification accuracy, precision, and recall for four classes classification are 85.5%, 85.25%, and 87.27%, respectively. The additional data training may improve the success rate, especially for fresh/excellent class.

Table 4. Confusion matrix for four classes classification

Data testing		Confusion matrix				Recall	Precision	F-measure	Accuracy (%)
		p-excellent	p-good	p-acceptable	p-spoiled				
d_0	t-excellent	36	107	0	0	25.17	100.00	40.22	83.71
	t-good	0	105	0	0	100.00	47.95	64.81	
	t-acceptable	0	7	130	0	94.89	100.00	97.38	
	t-spoiled	0	0	0	315	100.00	100.00	100.00	
		p-excellent	p-good	p-acceptable	p-spoiled				
d_1	t-excellent	142	0	0	0	100.00	100.00	100.00	87.29
	t-good	0	106	0	0	100.00	100.00	100.00	
	t-acceptable	0	0	46	0	100.00	34.07	50.83	
	t-spoiled	0	0	89	317	78.08	100.00	87.69	
			Average			87.27	85.25	80.12	85.50

Satisfactory accuracy is shown in binary classification (93.64%). However, the accuracy decreases as the number of classes increases (86% for three classes and 85.5% for four classes). The drawback of the proposed system is low recall in fresh and excellent classes. It also yields low precision in semi-fresh, good, and acceptable classes. Thus, the better method is necessary to deal with multiclass beef quality classification. Another drawback, the data analysis is still done offline using MATLAB 2015a.

4. Conclusions

We have been introduced the development of MoLen for beef quality monitoring and detection in this paper. It is developed under the low-cost hardware. In regards to the meat standard, this system demonstrates the promising performance to classify two, three, and four classes of beef quality using simple machine learning technique (k-NN). These experimental results show that this proposed system has good prospects for further development to present a low-cost, easy to use, and real time meat/beef quality monitoring. However, the low precision and recall in multiclass classification implies that the performance still needs to be improved. For future work, more advanced machine learning algorithms will be developed and additional data training is used to improve the system performance especially for multiclass classification.

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