Fish Freshness Testing with Artificial Neural Networks

Ayten Atasoy[1], Umit Ozsandikcioglu[1], and Selda Guney[2]

[1]Department of Electrical and Electronics Engineering, Karadeniz Technical University, Trabzon, Turkey
ayten@ktu.edu.tr, umitozsandikci@ktu.edu.tr
[2]Department of Electrical and Electronics Engineering, Baskent University, Ankara, Turkey
seldaguney@baskent.edu.tr

Abstract

In this work, with the use of an electronic nose which has 8 metal oxide gas sensors and was set up at Karadeniz Technical University, a fish freshness system was designed. There are 7 classes (1, 3, 5, 7, 9, 11, 13 day for fish storage) for classification and to perform classification process, Artificial Neural Networks was used in this work. To increase the classification success, Artificial Neural Network architecture, activation functions and input data obtained from different feature extraction method was changed, the storage condition is very important factor for fish freshness and fishes used in this study were stored at fish market conditions. In this study to determine the classification success, 5-Fold Cross Validation method was used and the maximum success rate was obtained as 98.94 %.

1. Introduction

After a while, environmental effects cause some physical, chemical, and biological reactions on fishes. As a result, amount of some chemical compounds raises or decreases in environment. Especially amount of dimethylamine (DMA), trimethylamine, ammonia, dopamine and histamine can increase when fishes become stale [1]. Great amount of these chemicals are very harmful for human health. Changes in amount of these compounds can be detect with electronic noses and with the use of proper pattern recognition techniques, freshness of fish can be determined very effectively [2].

Not only detect the fish freshness but also to detect quality of other foods, electronic noses can be used. While tea quality can be control with electronic noses, milk, meat and wine quality can be control very successfully with electronic noses too [3].

The electronic noses consist of three main components, these are sensor unit, electronic unit and pattern recognition unit. In sensor unit, sensors convert chemical changes result of chemical compounds from odor source to electrical signals. 8 MOS sensors were used in this study and features of them can be seen in Table 1. Signals from sensor unit can be processed in electronic unit with appropriate circuits. For example these signals can be amplified or can be filtered. Then these signals are sent to pattern recognition unit to be classified for correct class.

In food and beverage sector electronic noses are used widely. For example, in a study the shelf life of European sea bass was determined with electronic nose at three different temperatures [4]. In other study, using the transient response of each sensor, freshness of sardine stored at 4 °C were monitored and the fishes were classified to three classes and success rate of classification reached to 96,60 % and 96,88 % with Discriminant Factor Analysis and Fuzzy ARTMAP method respectively [5].

Table 1. Sensors used in the experiment

No	Sensor Name	Target Gases
1	TGS 880	Cooking Vapors
2	TGS 2620	Organic Solvents
3	TGS 825	Toxic Gases
4	TGS 2602	Indoor Pollutants
5	TGS 826	Toxic Gases
6	TGS 2104	Automobile Ventilation
7	TGS 830	Chlorofluorocarbons
8	TGS 2610	Combustible Gases

Sardines were examined in another work and in this study evolutionary stages of sardines were monitored. These sardines were stored up to 1-week at 4 °C. Classifying success was obtained with a support vector machine based classifier 100 % for three classes as medium and outdated. [6]. In another work, with two electronic noses which have different number of sensor and sampling systems, freshness of cod-fish fillets were measured and in this work misclassified samples were reduced to 4 % [7]. Moroccan sardines were examined in another work too, and a portable electronic nose with six tin oxide based taguchi gas sensor were used. With Principal Component Analysis (PCA) and Support Vector Machines (SVM) methods fresh sardines were identified from aged sardines with 100 % success rate [8]. Horse mackerel freshness was examined by using an electronic nose as well. The electronic nose with 8 metal oxide gas sensor was tried to classify the fish freshness in 7 classes. The fishes used in that work were stored at fish market conditions. Success rate was obtained as 97.22 % with combination of k-Nearest Neighbour (k-NN) and Support Vector Machines (SVM) in decision tree structure [9]. In another other study, for fish freshness assessment systems, researchers used a portable electronic nose with 32 sensors. They obtained 91 % success rate with artificial neural networks (ANN) [10].

Since Horse mackerel (trachurus trachurus) used in this study is very widely consumed in Turkey, its freshness is very important too. The shelf life of a fish is not long, so it must be consumed early as far as possible. Also a stale fish has very adverse effects on human health [1].

The electronic nose used in this study is consist of 8 metal oxide gas sensors and with the use of this electronic nose horse mackerels were classified to totally 7 classes. Different from other works, the fishes used in this study are stored at storage reservoir of the fish market and with this method, effect of fish market storage conditions can be seen more clearly.

2. Material and Methods

2.1. Raw Materials

To collect data for odor recognition system, an electronic nose set up in Karadeniz Technical University was used.

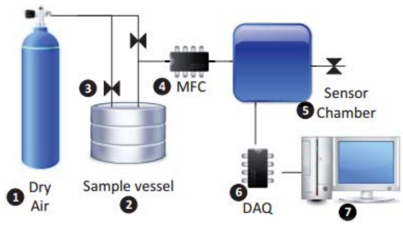
Horse mackerel is a fish species which can be live in Black Sea widely and fishes used in this work were purchased from a local fish market in Trabzon. At fish market, fishes are stored in a fish reservoir at 4 °C with ice. Difference this study from other works is storage conditions. The effect of fish market storage conditions on fish freshness can be monitored more accurately with this method. During this study 10 fishes were bought from fish market on average every day and totally 110 experiments were done.

2.2. E-nose set-up

The e-nose system used in this study consists of 8 metal oxide gas sensors and experimental set up of this e nose is shown in Fig. 1. The other parts of electronic nose are dry air tube, odor sample vessel, valves, mass flow controller, sensor chamber, DAQ and computer. Teflon tubes were used to move the odor throughout system. Therefore the effect of previous odor was tried to minimize.

To transmit signals obtained from sensors, National Instrument DAQ 6259 device was used with sampling frequency 1Hz. This device has 16 differential BNC analog inputs (16-bit); 1.25 MS/s single-channel (1 MS/s aggregate), 4 BNC analog outputs (16-bit, 2.8 MS/s); 48 digital I/O (32 clocked, 8 BNC). Flow range of the MFCs can be calibrated with flow unit. Either flow rate of each gas stream or concentration of the mixed gas can be controlled. To control whole system working, data acquisition process and pattern recognition algorithms were performed with Matlab.

Each of experiments performed in this study was divided to 4 stages shown in Table 2, these are pre-purging stage, odor sampling stage, breathing stage and post purging stage. Total duration of these stages is equal to duration of an experiment with 600s.



(a)

(b)

Fig. 1. The e-nose system performed in Karadeniz Technical University. (a) Block Diagram of system,(b) Photograph of system

Table 2. Stage of Experiments

Stage Name	Period of stage (s)
Pre-purging stage	130
Odor sampling stage	30
Breathing stage	30
Post-purging stage	410

2.3. Artificial Neural Networks

Artificial Neural Networks, like biological neural systems, can be defined as an information transcription system and can be used for classification, pattern recognition, parameter estimation and optimization problems frequently [11]. The architecture of ANN depends on nature of problem and for each different problems, the architecture must be designed again. The basic element of an ANN is Artificial Neurons. These neurons multiple their inputs (xi) with variable weights and values obtained from this process transform with an activation function (f(.)) to output value (yi). These operations can be seen in equation (1) and (2).

$$\sum_{i=1}^{p} w_i * x_i + b \quad (1)$$

$$y = f(net) = f(\sum_{i=1}^{p} w_i * x_i + b) \quad (2)$$

ANN uses input and output values and determines error value. To decrease the error value, ANN changes its bias values and therefore response to new input data new output value determines more accurately.

Generally, artificial neurons come together in layers and Multilayer Artificial Neural Networks consist of combining of these layers. Network's topology, activation function and training method mainly characterize artificial neural network architecture.

2.4. Data Analysis

In this study, before feature extraction and classification stages, signal pre-processing was performed. Since dry air was used to carry the fish odor, carrier gas was subtracted from raw signal. Thus the effects of the sensor drift were reduced. These operations can be seen in (3).

$$V_d(t) = V_s(t) - V_c(t) \quad (3)$$

In (3) $V_s(t)$, $V_c(t)$ and $V_d(t)$ represent voltage signals of sensor data, carrier gas data and difference data respectively. Therefore, the effect of carrier gas is minimized. The previous works show that success rate of study is increased with the use of difference data in the classification stage. Sensor drift is very important for classification problems with electronic nose too and one of the effective methods to solve this problem is baseline manipulation process [12]. In this study, the difference signal was extracted from the initial value of difference signal, this process can be seen in (4).

$$V_{db}(t) = V_d(t) - V_d(0) \quad (4)$$

In (4), $V_d(0)$ and $V_d(t)$ represent the initial voltage signal of sensors and difference signal respectively. Since in the presence of odor conductance of sensors are changed and conductivity of sensors are used often in literature, instead of voltage signal obtained from sensor, conductance of sensor was used in this study. Therefore voltage signal was converted to conductance signal with the use of (5).

$$G_s = \frac{V_{db}}{(V_c - V_{db})R_L} \tag{5}$$

In (3), R_L represent load resistor of sensors, G_s is conductance of sensors which changes with gas applied. In Fig. 2 and Fig. 3, the raw and preprocessed signals belong to 11th day can be seen respectively.

After obtaining of conductance signals, the features used for classification must be extracted. The feature extraction methods depend on nature of study but there is a common advantage that is reducing data size. For feature extraction process in this study, sub sampling method was used.

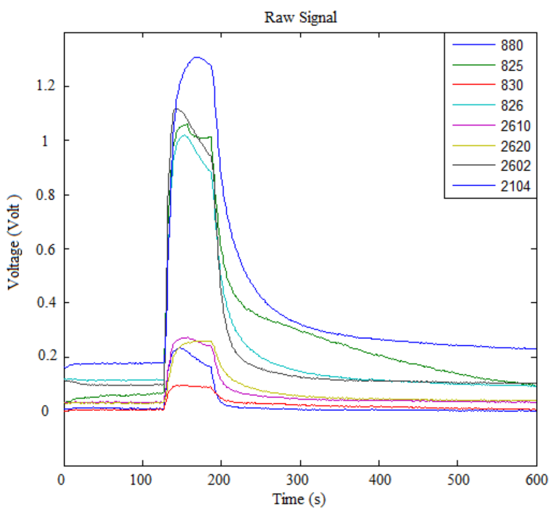


Fig. 2. The raw signal of 11th storage day for fish

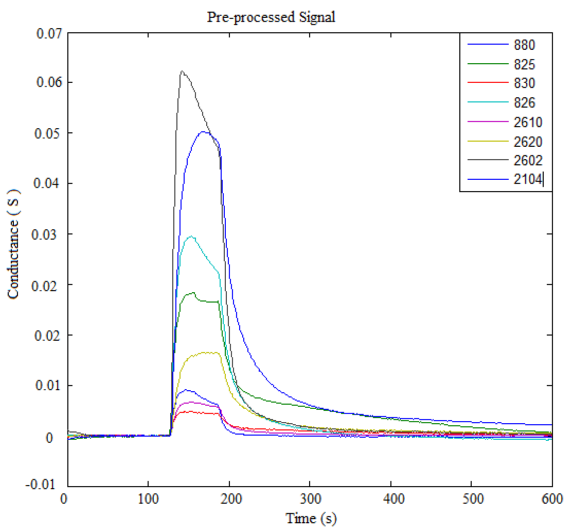


Fig. 3. The pre-processed signal of 11th day

In this study totally 600 data samples were obtained from volatile organic compounds (VOCs) of each fish. In the feature extraction process, different features are extracted such as the maximum, minimum and standard deviation values of sensor responses are extracted for each data signals. Therefore, every VOC has 8 features for each parameter (maximum, mean, standard deviation) since 8 sensors were used. The success of classification for fish freshness testing was tested with 5-Fold cross validation method. When maximum values of sensors were used, the best classification result was obtained as 86.41%. Other performance results can be seen in Table 3.

Table 3. Features used and success rate

Extracted Features	Success Rate
Maximum	86,41
Mean	82,14
Standard Deviation	83,28

The other feature extraction method used in this study is sub selection method. For sub sampling, 10 data samples from different time intervals of the experiment were selected for each sensor signals. Data samples were chosen from four different time intervals for this method. Odor first applied to sensors at 130th second and sensors were started to clean at 190th second of experiment. Therefore data samples were selected from 130th – 220th second time interval. To collect first data set, data samples were chosen from 130th – 160th time interval, therefore the effect of first phase of sensor responses were investigated. Second data samples were chosen from 160th – 190th second time interval. Since both side of sensor chamber were closed during this interval, data samples from this interval give information about steady state response of sensors. Because sensors were started to clean at 190th second, third data set was chosen from 190th – 220th second time interval. Data samples from this interval can be shown the effect of cleaning phase of sensors on classification process. The last data set were chosen from 130th – 220th second time interval. Since VOCs of the fish were applied sensors at 130th second and sensors were started to clean at 190th second, information in this interval and parts of this interval is important for classification process. To collect dataset, 10 data samples were chosen from each sensor signals for each time interval. For each time interval 8x10= 80 data samples were obtained for each odor signals of fish. Box plots were used to show the difference of sensor responses belong to 5th storage day and 11th storage day for fish in Fig. 4 and Fig. 5 respectively. For example while conductance values of 8th sensor range from 1 to 4 mS in Fig. 4, in Fig 5 conductance values of 8th sensor range from 50 to 90 mS. Other differences about sensor responses for 5th and 11th storage day for fish can be seen in Fig. 4and Fig.5. In these figures data samples from 160^{th-}220th second time interval were used. In these figures, the range of distribution for each sensor responses and difference between the responses are clearly seen for 5th storage day and 11th storage day for fish.

10 data samples were chosen from 130s-160s, 160s-190s, 190s-220s and 130s-220s time intervals with sub-sampling method and these data samples were used as input data for ANN respectively. Classification results for each time interval is given in Table 4.

Table 4. Time interval and sucess rate

Time Interval (s)	Success Rate (%)
130-220	72,99
130-160	84,39
160-190	98,94
190-220	83,34

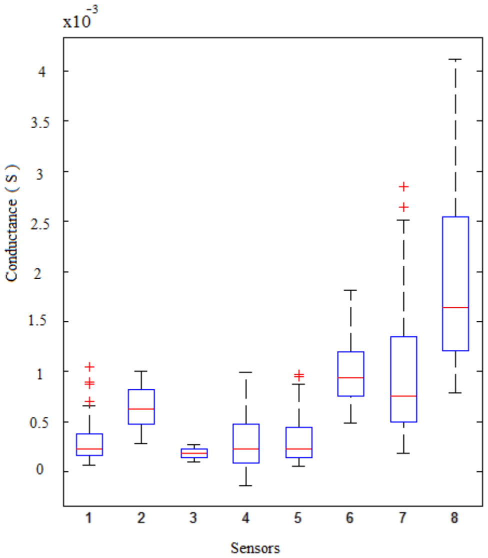


Fig. 4. Box plot of 5th storage day for fish

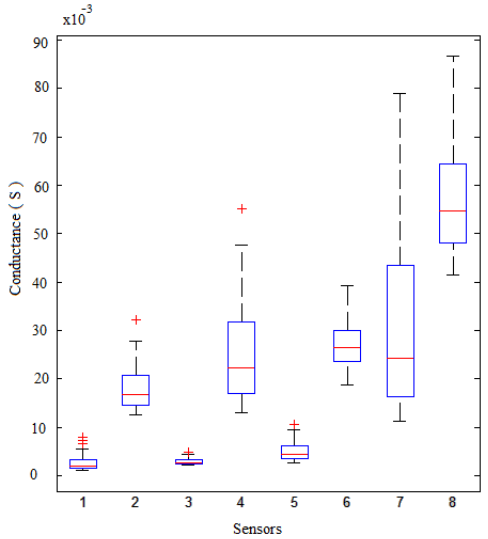


Fig. 4. Box plot of 11th storage day for fish

5 Fold cross validation method was used to determine the classification success rate. To perform 5-Fold Cross Validation method, totally 280 data samples was used from each time interval and these samples were divided 5 equal parts and to determine the success rate each experiment was performed 20 times. The success rate versus time interval of experiment is shown in Table 4.

3. Conclusions

In this study, ANNs were used to classify fish freshness to 7 classes (1, 3, 5, 7, 9, 11, 13 storage days). To increase classification success ANN architecture has an important effect on system performance besides data sample type. Therefore different ANN architectures used. For example, number of neurons in hidden layer was chosen as far as minimum to increase success and decrease operation duration and best number of these neurons was obtained with 8-8-7 as number of neurons in input layer, hidden layer and output layer respectively. To choose the proper activation function in hidden layer and output layer, experiments were repeated and in this study best activation combination was obtained with Tangent Sigmoid (tansig) and tansig in hidden layer and output layer respectively. When Logarithmic Sigmoid Function was used in output layer, classification success rate decreased down to 40 %.With this result the importance of activation functions in ANN can be seen clearly. About other parameters, learning rate was 0.5 and learning algorithm was chosen Bayesian Regulation (tranbr). All this values were obtained with experiments during classification operation. As mentioned in Table 4, when data samples from 160s-190s time intervals were used as input data to a fed forward artificial neural network, classification success rate increased up to 98.94 %.

4. References

[1] M. L. Rodriguez-Mendez, M. Gay, C. Apetrei, J. A. De Saja, “Biogenic amines and fish freshness assessment using a multisensory system based on voltammetric electrodes. Comparison between CPE and screenprinted electrodes” Electrochimica Acta, vol. 54, pp. 7033–7041, November 2009.

[2] A. Loutfi, S. Coradeschi, G. K. Mani, P. Shankar, John B. B. Rayappan., “Electronic noses for food quality: A review”, Journal of Food Engineering, vol. 144, pp. 103-111, January, 2015.

[3] N. El Barbri, A. Amari , M. Vinaixa , B. Bouchikhi , X. Correig , E. Llobeton, “Building of a metal oxide gas sensor-based electronic nose to assess the freshness of sardines under cold storage”, Sensors and Actuators B, vol.128, pp. 235-244, December, 2007.

[4] S. Limbo, N. Sinelli, L. Torri, M. Riva, “Freshness decay and shelf life predictive modelling of European sea bass (Dicentrarchus labrax) applying chemical methods and electronic nose”, Food Science and Technology, vol. 42, pp. 977-984, June, 2009.

[5] N. El Barbri, A. Amari, M. Vinaixa, B. Bouchikhi, X. Correig, E. Llobet, “Building of a metal oxide gas sensor-based electronic nose to assess the freshness of sardines under cold storage”, Sensors and Actuators B, vol. 128, pp. 235-244, December, 2007.

[6] N. El Barbri, J. Mirhisse, R. Ionescu, N. El Bari, X. Correig, B. Bouchikhi, E. Llobet, “An electronic nose system based on a micro-machined gas sensor array to assess the freshness of sardines”, Sensors and Actuators B, vol. 141, pp. 538-543, September, 2009.

[7] C. Di Natale, G. Olafsdottir, S. Einarsson, E. Martinelli, R. Paolesse, A. D’Amico,“ Comparison and integration of different electronic noses for freshness evaluation of cod-fish fillets”, Sensors and Actuators B, vol.77,pp.572-578, June,2001.

[8] N. El Barbri, E. Llobet , N. El Bari , X. Correig , B. Bouchikhi, “Application of a portable electronic nose system to assess the freshness of Moroccan sardines”,

Materials Science and Engineering C, vol.28, pp.666-670, July, 2008.

[9] Atasoy A., Güney S., "Fish Freshness Assessment By Using Electronic Nose", 36th International Conference on Telecommunications and Signal Processing (TSP), Rome, ITALIA, 2 - 4 June 2013, pp.742-746.

[10] H. GholamHosseini , Dehan L., Hongxiu L., Guanggui X., " Intelligent Processing of E-nose Information for Fish Freshness Assessment " , Intelligent Sensors, Sensor Networks and Information, December, 2007.

[11] Hamzacebi, C., Yapay Sinir Ağları: Tahmin Amaçlı Kullanımı ve Neurosolutions Uygulamalı, Ekin Yayınevi, Bursa, 2011.

[12] Gutierrez-Osuna and H.T. Nagle, "A Method for evaluating datapreprocessing techniques for odor classification with an array of gas sensors", IEEE Transactions On Systems, Man, And, Cybernetics-Part B, vol. 29(5), pp. 626-632, 1999.