Fusion Technique for Honey Purity Estimation using Artificial Neural Network

Norazian Subari[1] Junita Mohamad Saleh[2] Ali Yeon Md Shakaff[3]

School of Electrical and Electronic Engineering,Universiti Sains Malaysia
14300 Nibong Tebal, Pulau Pinang, Malaysia
[1]aziansubari@gmail.my
[2]jms@eng.usm.my
Centre of Excellence for Advanced Sensor Technology (CEASTech),
Universiti Malaysia Perlis (UniMAP), 0100 Kangar, Perlis, Malaysia
[3]aliyeon@unimap.edu.my

Abstract

This paper presents the estimation of purity of honey using Artificial Neural Network (ANN). ANN method was used to automate the decision of estimation, replacing the manual human approximate method. A total of 21 honey purity samples from various concentrations of pure honey, adulterated honey and pure sugar were collected. The data were collected using electronic nose (E-nose) and Fourier Transform Infrared (FTIR). Fusion method was applied in this work by combining the variable from both E-nose and FTIR to produce new sets of data. This data were used as input parameters for ANN learning. The results show that ANN was able to estimate the concentration of honey purity in adulterated honey solution with less error using fusion data as compared to single modality data.

Keywords: E-nose, FTIR, Fusion, Artificial Neural Network

1. Introduction

Malaysia is a tropical country is located in South East Asia. It is rich in natural forest resources such as honey. Honey is a viscous, supersaturated sugar solution derived from nectar gathered and modified by honeybee (Apis dorsata). According to the European Union (EU) regulations [1], the food Codex Alimentarius [2] and various other international honey standards, honey stipulates a pure product that does not allow for the addition of any other substance.

Honey is a traditional food. It is a source of sweet food and it can be consumed by all ages from infant to the elderly. As a natural multivitamin, honey has benefit for pregnant mother to keep their stamina and health. Due to its high carbohydrate content, honey is an excellent source of energy or supplement for athlete [3]. Since ancient times, honey has been used in medicine as well as doctor and surgeon used honey in their medical practice and even recommended its use. Honey has been proven to be effective in the treatment of burns, ulcers and wound [4-5].

Currently, the market demand for honey is very high as people are becoming more aware of its benefits for health. This has resulted in increased production of adulterated honey claimed as pure honey by irresponsible parties. Many manufacturers have started to add variants of sugar in pure honey that it has become difficult to differentiate pure honey samples from adulterated ones.

Quality assessment of honey is often related to its flavor, chemical contents and nutritional values. Unfortunately, analytical procedure such as Liquid Chromatography-Mass Spectrometry (LC-MS) and Gas Chromatography- Mass Spectroscopy (GC-MS) are limited to chemical separation [6-9]. These laboratories assessment are useful and accurate but they have drawbacks such as being time-consuming and requiring highly skilled operators to perform [10].

This paper presents two honey sensing modalities, namely electronic nose (E-nose) and Fourier Transform Infrared (FT-IR) for obtaining data of adulterated honey. These modalities are combined by an effective data fusion algorithm for the task of estimating the level of purity of honey. The aim of this work is to investigate the feasibility of the fusion method coupled with ANN for estimating the level of honey purity in adulterated honey solution.

2. Methodology

The intelligent honey estimation system work stages involve honey sample preparation, data acquisition and ANN system for estimation task. The estimation system was developed using Matlab R2010a. The following subsections discuss the methods involved in this work.

2.1. Sample preparation

Ten different brands of Tualang honey were purchased from local market with three different batches of each particular honey. Out of each bottle, three 5-mL samples were taken for analysis.

As adulterated purposes, two types of organic sugar solution have been used in this experiment; beetroot sugar obtained from Grafschafter Krautfabrik (Meckenheim, Germany) and cane sugar obtained from Lyle Golden Syrup (Bristol, United Kingdom). 5-mL sample of each sugar solution were prepared as pure sugar sample. Nineteen level of adulterated sample were prepared for each sugar solution as shown in Table 1.

Table 1: Production of adulterated honey samples.

Percentage of pure honey	Ratio of pure honey / sugar solution	Label for Honey + Beetroot Sugar (BS)	Label for Honey + Cane Sugar (CS)
5% pure	1:20	05BS	05CS
10% pure	2:20	10BS	10CS
15% pure	2:20	15BS	15CS
20% pure	4:20	20BS	20CS
25% pure	5:20	25BS	35CS
30% pure	6:20	30BS	30CS
35% pure	7:20	35BS	35CS
40% pure	8:20	40BS	40CS
45% pure	9:20	45BS	45CS
50% pure	10:20	50BS	50CS
55% pure	11:20	55BS	55CS
60% pure	12:20	60BS	60CS
65% pure	13:20	65BS	65CS
70% pure	14:20	70BS	70CS
75% pure	15:20	75BS	05CS
80% pure	16:20	80BS	10CS
85% pure	17:20	85BS	05CS
90% pure	18:20	90BS	10CS
95% pure	19:20	95BS	05CS

2.2. Data Collection

Two types of modalities have been used in collecting honey data. There are Electronic nose (e-nose) and Fourier Transform Infrared (FTIR).

2.2.1. E-nose

The e-nose used was a Cyrano Science Cyranose 320. It is a portable system from Smith Detetction^{TM} (Pasadena, CA, USA) consisting of 32 individual polymer sensor blended with carbon black composite. They are made up of various conducting polymers to sense a variety of vapor mixtures. The filter used is made of activated carbon granules and had a large surface area, making it effective in removing a wide range of volatile organic compounds and moisture in the ambient air. The setting on the sniffing cycle of the Cyranose 320 (C320) is as indicated in Table 2. Each sample was drawn from the bottle using 10-mL syringe and kept in a 13x100-mm test tube and seal with a silicone stopper. Before measurement, each sample was placed in a heater block and heat up for 10 minutes to generate sufficient headspace volatile.

Table 2: E-nose parameter setting for honey, sugar concentration and adulterated sample assessment.

Cycle	Time (s)	Pump Speed
Baseline Purge	10	120mL / min
Sample Draw	40	120mL / min
Idle Time	3	-
Air Intake Purge	40	120mL / min

2.2.2. FTIR

FTIR spectral measurements were gathered at room temperature of 27 ^{0}C using a Perkin Elmer 1600 FTIR Spectrometer (Waltham, MA, USA). This FTIR Spectrometer is equipped with ATR crystal having coverage of the 4000 to 650 cm^{-1} spectral region. The spectral measurements were performed against a background baseline of distilled water and presented in total attenuation units. The crystal surface was cleaned with distilled water and dried with tissue paper (Kimberly-Clark, Selangor, Malaysia) after the measurement of each sample. The background spectrum obtained from the first measurement was verified through the spectrum waveform to ensure the surface of the crystal was cleaned and free from previous sample residue. Then, a small drop of honey sample was placed on the crystal using a syringe and measurements were taken. Each sample was scanned four times and the measurements were averaged.

The spectral data were processed using FTIR spectroscopy spectrum software version 5.0.1 by Perkin Elmer for baseline correction, smoothing and normalization. Baseline correction is a process of removing background noise by eliminating the dissimilarities between spectra due to shifts in baseline. Smoothing is essential to reduce high frequency instrumental noise and enhance information content of a spectrum. Normalization of spectra eliminates the path length variation and reduces the differences between measurements of a single sample. Usually the spectra are normalized to the most intense band or at the same integrated intensity within a given spectral region [11].

2.3. Data Pre-processing

E-nose data acquired by the Cyranose 320 is a set of relative changes in the resistances of the polymer composites sensors during exposure to the gas of interest. Firstly, all the e-nose data were preprocessed automatically in MATLAB using the fractional measurement technique known as baseline manipulation. Using this technique, new sets of pre-processed data, *Sfrac* were obtained based on equation (1):

$$Sfrac = [St - S0] / S0 \qquad (1)$$

Where $S0$ is the minimum value taken during baseline purge with ambient air and St is the sensor response obtained in a sample draw. As each sensor has large varying levels of response, this equation gives a unit response for each sensor array according to its baseline. Therefore, the effect of temperature, humidity and temporal drift could be minimized [12]. Few works have reported on features extraction from FTIR spectra. In this work, the corrected peak height method used in feature extraction as commonly applied in medical [11, 13- 14]. The selection of features (corrected peak height) is based on the functional class contained in honey sample used. Based on the sample plot, five peaks were selected as salient features for detection of honey adulteration. The selected features are the corrected peak height at 919 cm^{-1}, 1031 cm^{-1}, 1415 cm^{-1}, 2933 cm^{-1} and 3265 cm^{-1}.

2.4. Data Fusion

Data fusion is a technique of combining data from multiple sensors or modalities. This technique has been shown an improvement of the system performance compared by using single modality [15-19].

In this experiment, low level fusion was investigated. This fusion technique does not require the same number of features form both modalities. This work simply combined them into a single vector for task. The fusion of FTIR (five features) and e-nose data (32 resistance values) gave a total of 37 signals for estimation task.

2.5. Development of ANN Honey Estimator

A commonly used ANN architecture, a multilayer perceptron (MLP) which learns using a back-propagation algorithm was employed. Figure 1 shows the structure of MLP neural network which has three layers; the input layer, hidden layer and output layer. Each layer consists of one or more nodes, represented by the circle. The lines between nodes indicate the flow of information from one node to the next. In this network, the numbers of inputs neurons were represented by the number of fusion signal. All 37 input variables then distribute their values to each of the neuron in the hidden layer.

In the hidden layer, the value from each input was fed into the network and training occurred by automatically adjusting the connection weights in order to reduce error. ANN training was terminated based on a validation set which validates the MLP performance. This avoids premature training as well as overtraining.

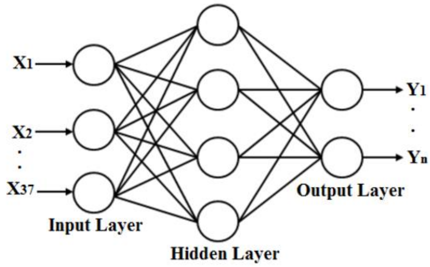

Fig. 1: Structure of MLP neural network.

Four combination of hidden and output activation functions were investigated in selecting the optimum threshold function in this work. The hidden activation functions used were logistic sigmoid (logsig) and linear transfer function (purelin).

3. Results and discussion

The combinations of the activation functions and their results are as listed in Table 3. The best performance was selected based on the lowest mean absolute error (MAE).

Table 3: Estimation Result for All Combinations.

Combination Label	MAE (%)
LL	12.6%
LP	6.9%
PL	12.6%
PP	7.0%

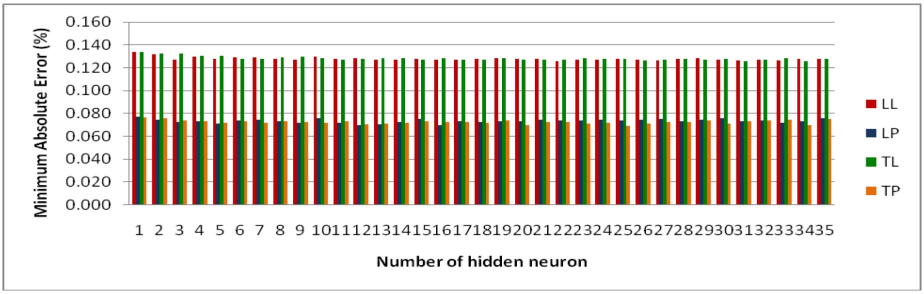

Fig. 2: Estimation result (MAE) based on hidden neuron.

Figure 2 shows the results of MAE for various numbers of various numbers of hidden neurons. It can be seen that the best number of hidden neuron is 12 with 6.9% MAE.

4. Conclusion

In this work, the feasibility of honey concentration using fused data method was investigated. In fusion method, thirty-two resistances of e-nose and five selected peaks of FTIR spectra were fused into a new signal of 32 resistances. These signals were used to train MLP ANN for the estimation task. The fusion method gave more accurate honey concentration estimation compared to single modality of either e-nose or FTIR.

Based on this study, the estimation MAE result of single modality based on e-nose or FTIR was 15.0% which is higher compared to fusion result. The fusion method gave 6.9% MAE of honey concentration estimation. This confirms superiority of fusion method at estimating pure honey concentration in adulterated honey solution.

Acknowledgement

This research is funded by the Universiti Sains Malaysia (USM) Short Term Research Grant Scheme No: 304/PELECT/60311038. The equipment used in this research was provided by the Universiti Malaysia Perlis (UniMAP). Authors also acknowledge Encik Ammar Zakaria for his help with data collection.

References

[1] CODEX STAN 12 Revised, Codex Standard for Honey, Codex Alimentarius Commision, 30:748-753, 2002.
[2] EU-Council Council Directive, Official Journal of the European Communities, L10:47-52, 2002.
[3] M. Blasa, M. Candiracci, A. Accorsi, M. P. Piacentini, M. Christina and E. Piatti, Adaptibe blind separation of sources: Raw Millefori honey is packed full of antioxidants, *Food Chemistry*, 97:217-222, Elsevier, 2006.
[4] A. Coulston, Honey….how sweet it is! , *Nutrition Today*, 35:96-100, 2000.
[5] T. Postmest, A. V. D. Bogaard and M. Hazen, Honey for wounds ulcers and skin graft preservation, *Lancet*, 341:756-757, Elsevier, 1993.

[6] L. R. Silva, R. Vedeira, A. P. Monteiro, P. Valentao and P. B. Andrade, Honey from Luso region (Portugal): Physicochemical characteristics and mineral contents, *Microchemical Journal*, 93:73-77, 2009.
[7] E. Anklam, A refiew of the analytical methods to determine the geographical and botanical origin of honey, *Food Chemistry*, 63:540-562, 1998.
[8] B. Plutowaska, T. Chmiel, T. Dymerski, and W. Wardencki, A headspace solid-phase microextraction method development and its application in the determination of volatiles in honey by gas chromatography, *Food Chemistry*, 126:1288-1298, 2011.
[9] L. F. Cuevas-Glory, J. A. Pino, L. S. Santiago and E. Sauri-Duch, A review of volatile analytical methods for determining the botanical origin of honey, *Food Chemistry*, 103:1032-1043, 2007.
[10] S. Roussel, V. Bellon-maurel, J. M. Roger and P. Grenier, Authenticating white grape must variety with classification model based on aroma sensors, FT-IR and UV spectrometry, *Journal of Food Engineering*, 60:407-419, 2003.
[11] Y. Jusman, N. A. M. Isa, S. N. Sulaiman and R. Adnan, Performance of Cervical Cell Spectra for Cervical Pre-Cancerous screening system using HMLP Network, *Proceedings of the Internationl Conference on Intelligent Network and Computing (ICINC 2010)*, pages 405-409, November 26-28, Kuala Lumpur (Malaysia), 2010.
[12] J. W. Gardner and P. N. Bartlett, A brief history of electronic noses, *Sensors and Actuator B*, 18-19:211-220, 1994
[13] Y. Jusman, N. A. M. Isa, S. N. Sulaiman, I. A. Yusoff, N. H. Othman and R. Adnan, Capability of new features from FTIR spectral of cervical precancerous diagnostic system using MLP networks, *Proceedings of 2009 IEE region 10 Conference (TENCON 2009)*, pages 405-409, January 23-26, Singapore, 2009.

[14] Y. Jusman, N. A. M. Isa, R. Adnan, and N. H. Othman, Intelligent classification of cervical pre-cancerous cells based on the FTIR spectra, *Ains Shams Engineering Journal*, 3:61-70, 2012.
[15] C. Li, P. Heinemann and R. Sherry, Neural Network and Bayesian network fusion models to fuse electronic nose and surface wave sensor data for apple defect detection, Sensor and Actuator B, 125:301-310, 2007.
[16] P. Boilot, E. L. Hines, M. A. Gongora and R. S. Folland, Electronic noses inter-comparison, data fusion and sensor selection in discrimination of standard fruit solutions, *Sensor and Atuator B*, 88:80-88, 2003.
[17] A. Zakaria, A. Y. M. Shakaff, A. H. Adom, M. Ahmad, M. J. Masnan and A. H. Aziz, Improved classification of orthosiphon stamineus by data fusion fruit solutions, *Sensors*, 10:8782-8796, 2010.
[18] N. Subari, J. M. Saleh, A. Zakariz, and A. Y. M. Shakaff, A hybrid sensing approach for pure and adulterated honey classification, *Sensors*, 12:14022-14040, 2012.
[19] A. Zakaria, A. Y. M. Shakaff, M. J. Masnan, M. N. Ahmad, A. H. Adom, M. N. Jaafar, S. A. Ghani, A. H. Abdullah, A. H. A. Aziz, L. M. Kamarudin, N. Subari, and N. A. Fikri, A biomimetic sensor for the classification of honeys of different floral origin and the detection of adulteration, Sensors, 11:7799-7822, 2011.