Australian Journal of Basic and Applied Sciences, 8(4) Special 2014, Pages: 593-600

AENSI Journals
Australian Journal of Basic and Applied Sciences
ISSN:1991-8178

Journal home page: www.ajbasweb.com

Mobile Olfaction System for Poultry Farm Malodour Monitoring

[1]A.H. Abdullah, [1]A.Y.M. Shakaff, [1]A.H. Adom, [1]A. Zakaria, [1]F.S.A. Saad, [1]N.A. Rahim, [1]K. Kamaruddin, [1]S.M. Mamduh, [1]J.M. Sah, [2]T.G. Teo

[1]*Centre of Excellence for Advanced Sensor Technology (CEASTech), Universiti Malaysia Perlis (UniMAP) Taman Muhibbah, Jejawi, 01000 Kangar, Perlis, Malaysia.*
[2]*Politeknik Sultan Abdul HalimMu'adzam Shah,06000Jitra, Kedah, Malaysia.*

ARTICLE INFO

Article history:
Received 20 November 2013
Received in revised form 24 January 2014
Accepted 29 January 2014
Available online 5 April 2014

Keywords:
Environment, malodour, mobile olfaction, multivariate statistical analysis, artificial neural network

ABSTRACT

Malodour from the poultry farm is an issue that often causes bitter relationships between farmers and local residents. The malodour triggers environmental issues with a potential health threat to animals and humans. This research proposes a fundamental study of poultry farm malodour monitoring using mobile olfaction system. The biological inspired system is an integration between a mobile robot and an electronic nose. The electronic nose consists of a sensor array, sensing chamber, microcontroller, signal conditioning and pattern recognition algorithm. The robot, using mecanum wheel, will manoeuvre through the environment while the e-nose acquires data. Artificial Neural Network (ANN) based on multilayer perceptron (MLP) is used to obtain the malodour concentration in real-time. The data acquired were transmitted and monitored wirelessly by a host computer for off-line data processing. Tests conducted showed that the system was able to navigate and conduct malodour concentration sampling in the environment.

To Cite This Article: A.H. Abdullah, A.Y.M. Shakaff, A.H. Adom, A. Zakaria, F.S.A. Saad, N.A. Rahim, K. Kamaruddin, S.M. Mamduh, J.M. Sah, T.G. Teo., Mobile Olfaction System for Poultry Farm Malodour Monitoring. ***Aust. J. Basic & Appl. Sci.,*** *8(4): 593-600, 2014*

INTRODUCTION

An unpleasant odour or malodour is caused by volatile chemical compounds which are pungent and smelly. The poultry farm malodour is an issue which has induced conflicts between farmers and nearby residents. The malodour dispersion is influenced by the quantity, moisture, temperature, wind and distances to human population (Gronauer, G., Neser, S. and Maier, B., 2003).

The malodour chemical compounds are also a potential health threat to the farm animals and humans. Ammonia (NH_3); the malodour main chemical compound, when at high concentration can cause dizziness and headaches (Barth, C.L., Elliot, L.F. and Malvin, S.W., 1984) while continuous exposure to carbon monoxide (CO) or methane (CH_4) can cause suffocation (Teye, F.K., Hautala, M., Pastell, M., Praks, J., Veermae, I., Poikalainen, V., *et al*., 2008).

The malodour is normally assessed by using human expert panels (olfactometry technique). Unfortunately, the panels are usually trained based on a fixed reference sample which is insufficient for the complexity of malodour from farms (Nimmermark, S., 2001).

The combination of electronic nose (e-nose) and mobile robot called mobile olfaction can be used as the alternative to perform similar tasks with less supervision and more reliability. The system's flexibility and ability to manoeuvrein difficult and isolated areas is important for the safety of humans in the area especially without adequate safety procedure (Pearce, T.C., Schiffman, S.S., Nagle, H.T. and Gardner, J.W., 2003).

Existing research on mobile olfaction mainly focused on navigation algorithm: odour detection, source localization and its distribution (Lilienthal, A.J., Loutfi, A. and Duckett, T., 2006). The biologically inspired techniques that had been used to detect the odour source are; trail following, plume tracking, and localization (Hayes, A.T., Martinoli, A. and Goodman, R.M., 2001). To date, the research areas of mobile olfaction have concentrated mainly in the applications of environmental monitoring (Gardner, J.W., Persaud, K.C., Gouma, P. and Osuna, R., 2012).

The use of commercial mobile robot such as Pioneer, Koala and Kephera was reported in the related literature (Lochmatter, T., Heiniger, N. and Martinoli, A., 2009; Martinez, D., Rochel, O. and Hugues, E., 2006). Some of the other robot manufacturers are SRV-1 Mobile Surveillance Robot, MOSRO from Robowatch and Patrol Bot (Lopez, J., *et al*., 2013).

This paper reveals the investigation of using mobile olfaction system for the detection and monitoring of

Corresponding Author: A.H. Abdullah, Centre of Excellence for Advanced Sensor Technology (CEASTech), Universiti Malaysia Perlis (UniMAP),TamanMuhibbah, Jejawi, 01000 Kangar, Perlis, Malaysia.
E-mail: abu.hassan@unimap.edu.my

poultry farm malodour. The robot will manoeuvre through the environment while the e-nose acquires data. The e-nose's embedded ANN network model was used to obtain the malodour concentration in real-time. The data acquired were transmitted and monitored wirelessly to a host computer. The system also has an *off-line* multivariate statistical analyserand ANN data processer. The system's portability and flexibility combined with cost efficiency provide advantages over the current techniques which are time-consuming and complicated. The information obtained by the system can be used by the farmer and local resident.

System Description:

The system architecture is shown in Fig. 1 where the e-nose is mounted at the front-end of the robot. The e-nose sampling process is effectively carried out when the position is facing the source of odour (Loutfi, A., 2006). The system is linked to a computer using XBee communication system to process the data and to monitor in real-time.

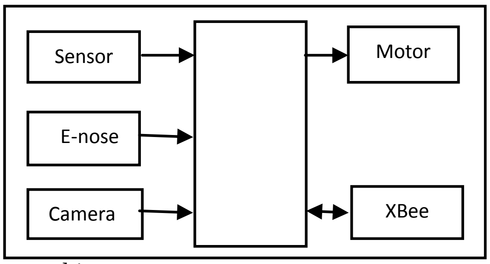


Fig. 1: The mobile olfaction system architecture

1. The Electronic Nose:

The e-nose; designed to mimic the human sense of smell, comprises of an array of chemical sensors and pattern recognition system. The instrument is capable of discriminating the sensor signals into classes corresponding to the chemical compound's *fingerprint* (Gardner, J. and Bartlett., 1994).

Most of the commercially available e-noses in the market are costly and unsuitable to be integrated with the robot. Hence, the development of a low-cost instrument equipped with embedded pattern recognition algorithm was initiated. The proposed instrument block diagram is shown by Fig. 2 which involves the design and fabrication of sensing chamber, microcontrollers board as well as signal conditioning and power supply circuits.

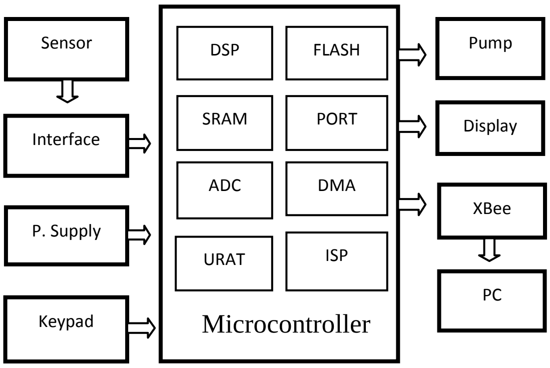


Fig. 2: The e-nose block diagram

More than 75 specific chemical compounds have been identified for poultry farms and the main chemical compounds are shown in Table 1 (Mackie, R.I., Stroot, P.G. and Varel, V.H., 1998). The table also shows the e-nose sensors which were used to detect the key chemical compounds.

Table 1: The e-nose sensors suitability for poultry farm

E-nose Sensor	Chemical Compounds
Ammonia	Ammonia, NH_3
Hydrogen sulphide	Hydrogen sulfide,H_2S
Gasoline / diesel engine	Nitrogen dioxide, NO_2
Methane	Methane, CH_4
LP gas	Propane, C_3H_8
Carbon dioxide	Carbon doixide,CO_2
Carbon monoxide	Carbon monoxide, CO
Air contaminants	Organic compounds
Water vapour	Water vapour
Temp. & humidity	Temperature & humidity

The e-nose uses an array of Metal-Oxide (MOS) gas sensor from FIGARO Engineering Inc., Japan as shown in Table 1. The sensors were used because of their high sensitivity, compact size and fast response time (Sandini, G., Lucarini, G. and Varoli, M., 1993). The relationship between sensor resistance and the concentration of the odour can be expressed by the following equation (Galdikas, A., Mironas, A., Senuliene, D., Strazdiene, V., Setkus, V. and Zelenin, D., 2000):

$$R_s = A[C] - ά \tag{1}$$

whereR_s is the electrical resistance of the sensor, A is constant, C is the odour concentration and ά is the slope of R_s curve.

The sensor array and its signal conditioning circuit's sensor is shown in Fig. 3**.** A sensing chamber and a 12-volt DC pump were used to concentrate the odour before being sensed by the sensor array. Each sensor in the array gives a different electrical response for a particular target chemical compound introduced into the sensing chamber. The combined output from the sensor array forms a chemical *fingerprint* corresponding to the sample.

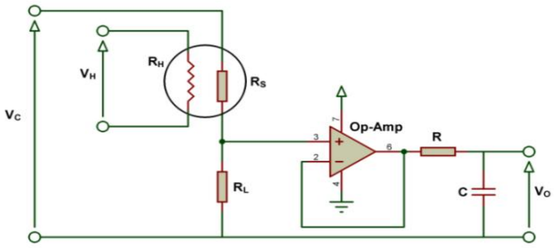


Fig. 3: The signal conditioning circuit

A humidity and temperature sensor, SHT-75 from Sensirion Technology was attached to the e-nose enclosure. The sensor communicates with the microcontroller board through Serial Peripheral Interface (SPI) communication. The e-nose uses a dsPIC33 microcontroller from Microchip Inc. to control the system and data processing as shown in Fig. 4 (Microchip Technology Inc., 2008). The dsPIC33 flash memory (256 KB) and RAM (30 KB) are capable of handling the data collection operation, system control and embedded neural network classification model.

Fig. 4: The microcontroller board

The e-nose was designed and modeled using SolidWorks software. The instrument enclosure was fabricated using Perspex as shown in Fig. 5. The material was selected because of its capability to withstand sensor heater high temperature.

Fig. 5: The e-nose prototype

The stand-alone e-nose has programs for control and classifies samples using the embedded classification model inside the microcontroller memory. The software has been developed on computer using MPLAB *C*

Compiler for *dsPIC* DSCs version 8.40 from Microchip Technology Inc. The menu driven software consists of data collection, classification and utilities.

The e-nose will acquire the sample data from the sensors' responses by utilising a customisedgraphical user interface (GUI) program on the computer. The window based GUI was used for user interface during data collection and system diagnostics.

The data processing algorithms are based on statistical and artificial neural networks (ANNs) technique which is done on the computer. The instrument also has embedded ANN utilising multilayer perceptron (MLP) classification model and is trained with the back-propagation error algorithm.

2. The Mobile Robot:

The mobile robot used in these investigations is custom made and is cheaper than a commercial robot, as shown in Fig. 6. The mobile robot chassis is made from aluminum plate to provide the system motion across the environment. The robot size is 38 cm wide, 46 cm long and 24 cm high.

The robot has omni-directional capabilities by using four mecanum wheels. The robot will be able to move efficiently in tight and isolated areas while navigating itself during the odour detection process (Minguez, J., 2005). Each wheel is independently driven by a 12-volt DC using Pulse Width Modulation (PWM) from the on-board microcontroller. The robot omni-directional locomotion will be the combination of each wheel movement as shown in Table 2.

Table 2: Robot movement

Robot Movement	Motor Movement
Forward	all four wheel move forward
Backward	all four wheel move backward
Right slide	wheel 1 and 4 forward, wheel 2 and 3 backward
Left slide	wheel 2 and 3 forward, wheel 1 and 4 backward
Clockwise	wheel 1 and 3 forward, wheel 2 and 3 backward
Counter-Clockwise	wheel 1 and 3 backward, wheel 2 and 3 forward

The robot uses the PIC18F2520 microcontroller interfacing board. The microcontroller embedded software was developed to control the robot navigation in real-time. The software was also used to communicate with the host computer through wireless communication. The robot was equipped with remote controller for manual mode.

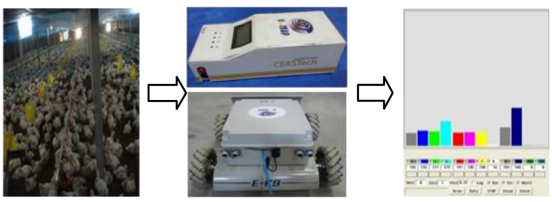
Three ultrasonic sensors were used for obstacles avoidance algorithm. The sensors were situated at the front-end of the robot to determine the distance between the robot and obstacles. The information from these sensors will be used by the robot to navigate through the environments.

The robot motions route based on the pre-determined location while manoeuvring through the environment. Any obstacle along the path will be sensed by the ultrasonic sensor and the obstacle avoidance algorithms will be applied. Then the e-nose will acquire the malodour sample at the location.

A wireless Charge Coupled Device (CCD) camera was also positioned at the robot front-end for visual information to monitor the environment remotely through the host computer. The robot utilises a 12-volt DC battery for its peripherals. In addition, an ultrasonic anemometer (WindSonic, Gill Instruments Ltd.) interfaces directly to the host computer to provide the two dimensional air speed and direction of the environment.

Methodology:

An experiment was conducted to verify the e-nose's sensitivity and detection limit that correlate with the malodour concentration. The samples were collected in a poultry farm in Malaysia. The samplings were done on the fourth week of the animals' 36-day breeding period. The process was conducted on-site at different locations in the animal barns and the surrounding areas. The samplings process is illustrated in Fig. 6. During the sampling process, the system was linked wirelessly with a host computer.



Sample Mobile olfaction GUI

Fig. 6: The sampling process

The sampling uses the *Sniff, Hold* and *Purge* technique whose parameter settings are shown in Table 3. This technique will *pre-concentrate* and '*Hold'* the malodour sample to enhance the instrument sensitivity. The selections for the duration for each of the operations were based on the MOS sensor characteristics and *trial and error* (Figaro Engineering Inc., 2005). The data were sent wirelessly to the host computer as shown by the system GUI in Fig. 6. The acquired data will be used for off-line data analysis capability by utilisingK-Nearest Neighbours (KNN) analysis and Artificial Neural Network (ANN) techniques.

Table 3: E-nose sampling parameter

Operation	Time (Sec)	Air Pump
Purge cycle	60	ON
Baseline correction	30	OFF
Sniff cycle	10	ON
Steady state response	80	OFF

RESULTS AND DISCUSSION

1. Sensor Response:

The responses of the sensors were plotted as a time series of waveform profiles and shown in Fig. 7. The sampling technique was suitable because the measured data did not vary significantly and were still within the *measurement range.* The response of the sensors indicated that the e-nose functions accordingly to the varying sample concentrations of different locations.

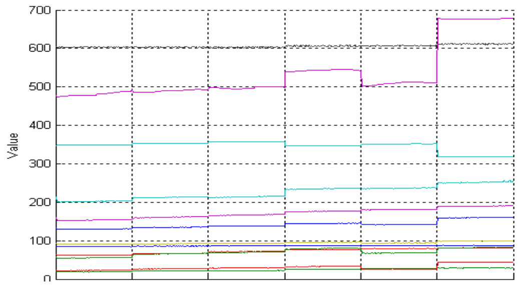


Fig. 7: Sensor response

2. Normality Test:

The normality test was used to investigate the data pattern using the three tests; Kolmogorov-Smirnov, Lillieforand Jarque-Bera methods. The test results are shown in Table 4 where in all of the tests the statistic value is greater than the critical value indicating that the distributions were not normal. So based on the finding, the non-parametric classification techniques should be used to analyse the malodour samples.

Table 4: The normality test

KSSat	KSCv	LilSat	LilCv	JBSat	JBCv
1.00	0.02	0,10	0.01	238.66	5.98
1.00	0.02	0.21	0.01	593.93	5.98
1.00	0.02	0.18	0.01	616.58	5.98
1.00	0.02	0.12	0.01	138.22	5.98
1.00	0.02	0.10	0.01	94.38	5.98
1.00	0.02	0.11	0.01	103.21	5.98
1.00	0.02	0.23	0.01	667.19	5.98
1.00	0.02	0.16	0.01	9.17	5.98
1.00	0.02	0.17	0.01	409.05	5.98
1.00	0.02	0.24	0.01	507.74	5.98
1.00	0.02	0.16	0.01	606.62	5.98
1.00	0.02	0.17	0.01	659.39	5.98

3. Principal Component Analysis:

The Principle Component Analysis (PCA) is an unsupervised technique used for clustering data according to groups. The PCA plots for the malodour samples are shown in Fig. 8. The two-dimension PCA plot was used because the first two Principal Components (PC) values were more than 90% of the total variances which contained most of the useful information. From the plots, the samples can be clustered into six different groups based on the different locations. The different group cluster shapes are not so curvilinear due to nonlinear data and the environment parameter effect.

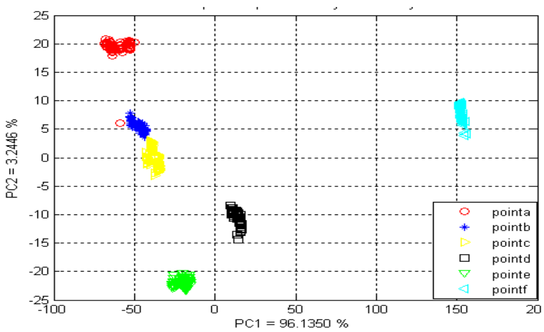


Fig. 8: The PCA plot

4. K-Nearest Neighbours (KNN):

The K-Nearest Neighbours (KNN) is a non-parametric technique for classifying samples based on their closeness to the training model. The simple machine learning algorithms are based on the distance between the unknown sample and the training model. Usually, the Euclidean distance is used, but for strongly correlated variables, correlation-based measures are preferred.

The KNN confusion matrix is shown in Table 5. The KNN performance in matrix-train and matrix-test was 100%. The data analysis results show that the e-nose performed well in classifying the sample. The Leave-One-Out (LOO) cross-validation was used to evaluate the KNN model's performance. The LOO cross-validation results are 100% indicating confirming that the KNN classification model's performance was correct.

Table 5: The KNN classification

Loc	Matrix-Test					
P1	30	0	0	0	0	0
P2	0	30	0	0	0	0
P3	0	0	30	0	0	0
P4	0	0	0	30	0	0
P5	0	0	0	0	30	0
P6	0	0	0	0	0	30

5. Artificial Neural Networks (ANN):

The Artificial Neural Networks (ANN) was used for its good adaptability property (learning, generalisation and noise tolerance) which is suitable for the non-linear data. It has the ability to learn the complex interaction between the malodour sample variables (Gardner, J.W., Hines, E.L. and Wilkinson, M., 1990). Three ANN classification models were used for the malodour sample; Multilayer Feed-Forward Perceptron (MLP), Probabilistic Neural Network (PNN) and Radial Basis Function (RBF).

The classification performance result for the malodour sample is shown in Table 6. All of the results for the three classifiers indicate that the tests classifications correlate with sample location. The results also indicate that the MLP, PNN and RBF classifier performance were almost equal. The results show that the mobile olfaction system was able to classify malodour samples according to their location.

Table 6: The ANN classification

ANN Types	Classification success rate (%)
MLP	99.69
PNN	100
RBF	100

6. Embedded Artificial Neural Network (ANN):

The embedded ANN MLP model was used to quantify the concentrations of sample malodours of the area. This strategy provides the system the ability of real-time monitoring of the odour over the operating area by identifying and quantifiying the malodour amount and location.

The results for the malodour concentration are shown in Table 7. The value was from 0.1 (very low) to 1.0 (extreme) based on the instrument's embedded ANN output. It was observed that the malodour concentration inside the chicken barn was higher than other locations. The ANN concentration results show that they are in correlation with the KNN results. This shows that the instrument was able to determine reliable malodour concentration for the farm surrounding areas.

Table 7: The embedded ANN classification

Location	Concentration
Point A	0.34
Point B	0.36
Point C	0.44
Point D	0.63
Point E	0.65
Point F	0.77

However, these results were influenced by the imprecise environment data and sensor drift (result of poisoning and aging). The effect is obvious for long sampling hours in changing field environment conditions.

Here, during the experiments, the measured data were compensated using baseline manipulation during data pre-processing. This baseline manipulation will improve the instrument's embedded ANN classification model robustness which was sufficient for the poultry farm malodour monitoring application.

The sytem can be improved by replacing the e-nose MOS sensor with other types of sensors to overcome the slow recovery process. This will meet the robot's real-time movement which improves the system's accuracy and efficiency.

The use of omni-directional wheel and obstacle avoidance navigation algorithm proves to be advantageous for the proposed system. The wheels gives the system high levels of maneuverability in confined spaces to move freely. A careful robot movement plan must be considered because the use of four DC motors, the e-nose and other peripherals will drain the system battery resources quickly.

Conclusion:

A mobile olfaction system prototype has been successfully developed using a mobile robot intregrated with an e-nose. The system algorithm which is capable of navigation through the environment in the presence of obstacles has been successfully developed. The system was successfully tested to detect malodour samples and the results indicate that it was able to fulfill the requirements of the poultry farm malodour monitoring.

Future work should consider adding a laser range finder at the robot front-end for mapping the environment which will smoothen the robot navigation.

ACKNOWLEDGEMENT

This project is partly funded by the Malaysian Ministry of Higher Education under the Prototype Research Grant Scheme (PRGS:9013-00007). A.H. Abdullah gratefully acknowledges the leave granted by Universiti Malaysia Perlis (UniMAP) to allow him to pursue his Ph.D.

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