Jurnal
Teknologi

Full Paper

MONITORING RUBBER FACTORY MALODOUR USING ARTIFICIAL NEURAL NETWORK

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Article history
Received
1 June 2015
Received in revised form
13 August 2015
Accepted
29 September 2015

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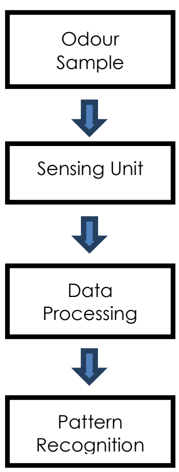
Graphical abstract



Abstract

Malodour from rubber factory activities is a nuisance to the residence in the surrounding area. The volatile chemical compounds emitted from the factory are identified as the major source of the malodour. This research proposes a study of malodour monitoring for the rubber factory using Electronic Nose (e-nose) system to enable effective malodour monitoring. The proposed system will able to predict and monitor the malodour concentration in the surrounding area of the factory. The finding will be used as a guideline for monitoring the violations of environmental guidelines. The malodour and environment parameters such as temperature, wind speeds and directions are recorded. These parameters are measured on-site and monitored using wireless sensor network (WSN) system. The malodour concentration model of each location will generate using three types of Artificial Neural Network (ANN) i.e. Multilayer Perceptron (MLP), Radial Basis Function (RBF) and Probabilistic Neural Network (PNN). These indices will be used to generate the malodour concentration mapping model of the factory and surrounding areas. The initial results show that the system can be effectively used for real time rubber factory malodour monitoring.

Keywords: Rubber factory malodour, electronic nose, artificial neural network, real time monitoring

Abstrak

Bau busuk daripada kilang getah adalah merupakan gangguan kepada penduduk di kawasan sekitaran. Sebatian kimia meruap yang dikeluarkan dari kilang dikenalpasti sebagai punca utama bau busuk ini. Kajian ini bercadang untuk memantau bau busuk dari kilang getah menggunakan Hidung Elektronik supaya proses pemantauan dapat dilaksanakan secara berkesan. Sistem yang dicadangkan akan dapat meramal dan memantau tahap bau busuk daripada kilang and kawasan sekitar. Hasil kajian boleh digunakan sebagai garis panduan untuk memantau alam sekitar. Sistem akan merekodkan bau busuk dan parameter persekitaran seperti suhu, arah dan kelajuan angin. Parameter ini diukur dilokasi dan dipantau menggunakan sistem rangkaian sensor tanpa wayar (WSN). Model kepekatan bau busuk setiap lokasi akan menjana menggunakan tiga jenis Rangkaian Neural Buatan (ANN) iaitu '*Multilayer Perceptron*' (MLP), '*Radial Basis Function*' (RBF) dan '*Probabilistic Neural Network*' (PNN). Indeks akan digunakan untuk menghasilkan model pemetaan tahap bau busuk tersebut. Keputusan awal menunjukkan bahawa sistem ini boleh digunakan dengan berkesan untuk pemantauan masa nyata bau busuk yang dikeluarkan oleh kilang getah.

Kata kunci: Bau busuk dari kilang getah, hidung elektronik, rangkaian neural buatan, pemantauan masa sebenar

1.0 INTRODUCTION

Malaysia is one of the main exporters of natural rubber in the world. But the malodour from rubber processing factories has threatens the industries. The main issue that causes the criticism from the public is the effects of malodour to environmental pollution that affect the workers health. The nuisance malodor emissions in the nearby populated areas often induced conflicts between residents and factory management.

Preventive measures should be taken to control the malodour emission from the rubber factory that affecting the surrounding areas. A malodour concentration prediction model will help in monitoring the environment pollution [1]. However, the malodour concentration prediction model is a complex process which involves the malodour and environmental parameters [2]. Human health, especially the factory workers and the surrounding population are affected by the air pollution [3].

A number of techniques are available to predict the malodour concentration model. One of the approaches is to use a diffusion model which eliminates the chemical equations and underlying physical to control malodour concentrations which require meteorological and emissions data [4]. Others will use statistical techniques to generate a regression model which will determine the relationship between targets and the data input [5].

A new technique is required to monitor the malodour concentration to control the emission. This paper proposes a system and method for rubber factory malodour monitoring using pattern recognition through Artificial Neural Network (ANN). The system can be used to monitor the malodour that will control the impact on humans and the environment.

2.0 NATURAL RUBBER (*HEVEA BRASILIENCES*)

Natural rubber is the material for a number of industrial components or products. The scientific name for natural rubber is *Hevea brasiliensis* and also called latex; an elastic hydrocarbon polymer. The chemical *polyisopropene* is synthetically produced from a purified rubber [6].

Table 1 Malaysia and Thailand Rubber Production

Item	Malaysia	Thailand
Rubber plantation (million hectares)	1.3	2
Natural rubber (million tons)	1.072	3.09
Global supply of natural rubber (percent)	10.7	33.5
Number of rubber factories	357	700

Table 1 as previous shows the rubber production between Malaysia and Thailand. These two countries are competing to become the main natural rubber producer in the world. Natural rubber latex contains almost 30% to 50% of Dry Rubber Content (DRC). This type of latex has been centrifuged to increase its DRC to 70% by removing water and other impurities.

The concentrated latex is used as a raw material for many rubber based products such as rubber glove. All latex is treated using 0.3 or 0.8% of ammonia solution, *Tetramethyl Triuram Disulfide* (TMTD), *Zinc Oxide* (ZnO) and *Diammonium Phosphate* (DAP) to extend its life, and to remove the magnesium by sedimentation prior to the centrifugation [7].

3.0 SYSTEM DESCRIPTION

3.1 System Component

The system is using an intelligent electronic sensing instrument known as electronic nose (e-nose) which mimics the human olfactory system to detect, discriminate and classify odour samples [8]. The instrument is suitable for non-destructive testing technique that produces a qualitative output. The rapid development of the instrument has been driven by its vast potential applications, which include food quality assurance, fragrance identification, environmental monitoring and plant disease detection [9, 10].

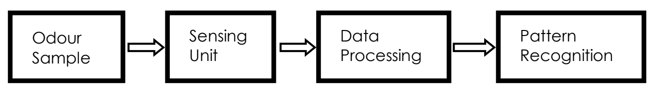


Figure 1 Electronic nose system

The basic concept of an e-nose is depicted by Figure 1. The sensing chamber function is to accommodate sensor arrays and interact with the odour sample. The chamber design process involves several factors such as internal structure, material selection, flow techniques and sensor cell type. The design should ensure that the odour sample are delivered simultaneously to sensor arrays for optimum induced process.

When the sensor arrays exposed to the odour sample, it will induce a chemical change in the sensing material and cause a change in conductance that convert into electrical signals [11]. The instrument sensor arrays will respond to different volatile compounds in varying concentration which generate a response pattern profile called *chemical fingerprint* which is related to odour sample concentration [12].

This odour sample *chemical fingerprint* will be used for the data processing. Some of the ideal sensor characteristics are as shown in Table 2 [13].

Table 2 Ideal sensor characteristics

Characteristics	Description
Sensitivity	The sensor sensitivity should be high at any sample concentration but low in humidity and temperature.
Selectivity	The ability to respond towards particular volatile compounds which value should be high.
Stability	The ability of the sensor to resist changes in different operating conditions.
Response time	The sensor response should be fast and rapid with short recovery time.

The instrument used an array of non-specific sensors with varying sensitivity for effective responses of the sample. The Metal Oxide Sensor (MOS) is the most typical sensors used by the instruments due to its features, which are low cost, long life, high sensitivity [14].

The number of sensors employed typically between five to twenty for maximise the number of target volatile compounds [15]. This will enable the instrument's data processing to generate a more robust classification model. The sensor selection process will select the high sensitivity to the odour sample volatile compounds for better instrument's detection limit. The process will exclude the non-perform and low-perform sensors. The process will also reduce the instrument's data processing computational complexity during classification that will increase the instrument's robustness.

The e-nose normally uses an embedded system with embedded software to control the instrument's operation and the odour sample pattern recognition using classification algorithm. The software is embedded in the instruments' memory and the classification process may perform concurrently with the control system. Normally microcontroller is used as the embedded system for its good processing capabilities and flexible connection to the system components.

3.2 Data Processing

The pre-processing will improve the acquired data quality by removing redundant and inappropriate information. The process will remove outliers and noise while retaining the significant information [16]. The process will enhance the instrument pattern recognition performance. The baseline data manipulation method was used for pre-processing the acquired data. The method was based on the difference of sensor responses between ambient air (reference) and odour sample as shown by equation (1):

$$X_{bl} = X_m - X_0 \quad (1)$$

where, X_{bl} is the baseline manipulation data, X_m is the odour sample data and X_0 is the ambient air (reference).

The normality test was used to identify the acquired data either parametric or non-parametric by using *Kolmogorov-Smirnov, Lilliefor and Jarque-Bera* methods. The test will identify the correct classification technique for the data processing.

Information from the literature review determine that the e-nose acquired data are non-linear. The data processing using pattern recognition technique usually use Artificial Neural Network (ANN) that has good learning, generalisation and noise tolerance [17]. Some of the ANN techniques normally used by the instrument are Multilayer Feed-Forward Perceptron (MLP), Probabilistic Neural Network (PNN) and Radial Basis Function (RBF) [18]. The ANN model was trained *offline* using MATLAB windows based software (version 2011, Mathworks, USA) for the odour sample classification.

The MLP is an establish technique due to its simplicity and easy operation [19]. Several activation functions can be selected to transform the output to limited value to be processed by the next layer.

The PNN is a statistical kernel discriminant analysis that organised in a multi layered feed forward network. The technique has good training speed with consistent classification result [20].

The RBF approximation capabilities are based on superposition of local models of the response system. The technique advantage is that the network has no local minima problem.

4.0 METHODOLOGY

Design of Experiment (DOE) technique was used for the data collection process. The experiments were conducted in March 2014 at the Malaysian Agricultural Research and Development Institute (MARDI) rubber factory in Perak Malaysia.

The odour sampling process uses static headspace technique as shown in Figure 2 where the e-nose was linked wirelessly with a notebook for the data acquisition process. The samplings were conducted on-site at the rubber factory and the surrounding areas. The sampling process uses ambient air as the odour sample reference. The odour sample was acquired at six different selected locations point (locations A, B, C, D, E and F). The sampling process also acquired other environmental parameters, i.e. temperature and humidity. The sampling process was repeated at the same time of day and in the same climatic conditions to ensure data reproducibility and repeatability.

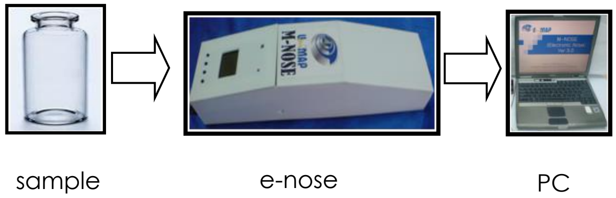


Figure 2 Block diagram of the processes of the system

5.0 RESULTS AND DISCUSSION

5.1 Sensor Array Response

The responses of the sensor array are plotted as a time series of waveforms profile and shown in Figure 3. Baseline manipulation was used for the data pre-processing. The sampling technique was suitable as the acquired data did not vary significantly and were still within the *measurement range*. The response of the sensor array shows that the instrument functions accordingly to the odour sample.

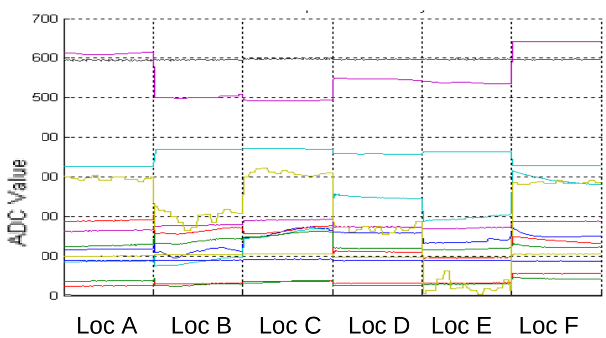


Figure 3 The baseline manipulation

5.2 Principal Component Analysis (PCA)

The Principal Component Analysis (PCA) was used to assess the linear separability of the acquired data. The result of PCA classification is shown by a graph plot in terms of component score, Principal Component (PC) and the group cluster. The PCA plots for the malodour sample are shown in Figures 4 to 7. The two dimensions (2D) PCA plot were used because the first two PC values were more than 90% of the total variances which contained most of the information. From the plots the samples can be clustered into six different groups based on the locations A, B, C, D, E and F. The different groups' cluster shapes are not so curvilinear due to the instrument's nonlinear data and environment parameter effect.

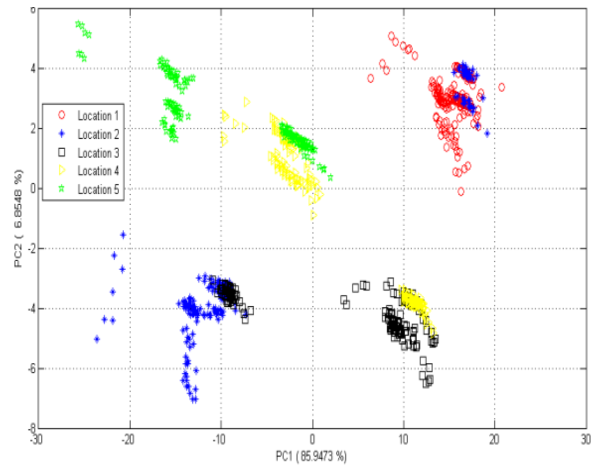


Figure 4 PCA plot for day one

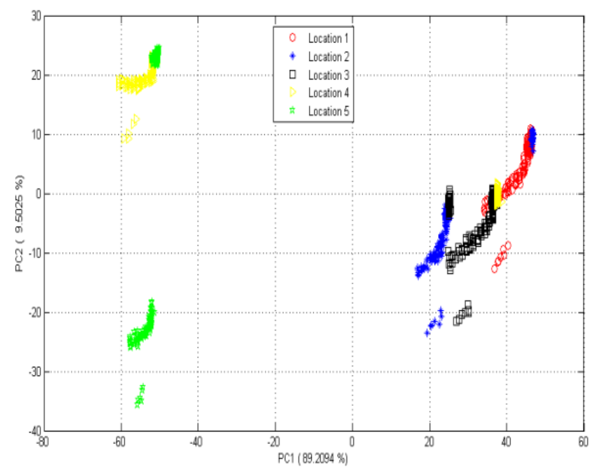


Figure 5 PCA plot for day two

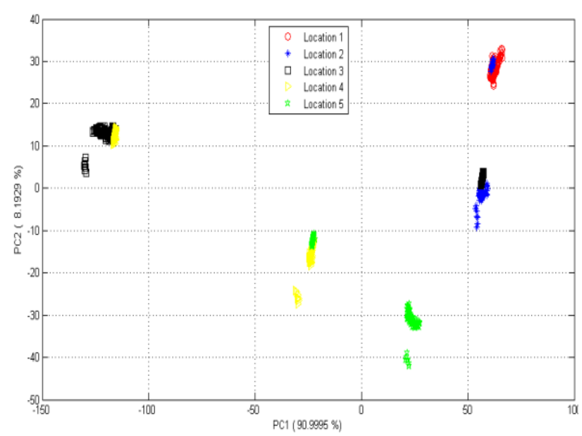


Figure 6 PCA plot for day three

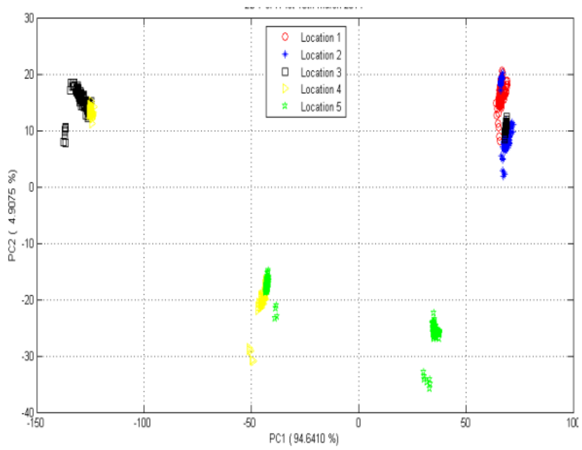


Figure 7 PCA plot for day four

5.3 Normality Test

The normality test was used to investigate the data pattern using the three tests; Kolmogorov-Smirnov, Lilliefor and Jarque-Bera methods. The test results are shown in Table 3 where for all of the tests the statistic value (KSSat, LiiSat and JBSat are the Kolmogorov-Smirnov, Liliefor and Jarque-Bera statistic value) is greater than the critical value (KSCv, LiiCv and JBCv are the Kolmogorov-Smirnov Liliefor and Jarque-Bera critical value) which indicates that the data distributions were not normal. So based on the finding, the non-parametric pattern recognition classification technique should be used to analyse the odour samples.

Table 3 The malodour sample data normality test

KSSat	KSCv	LilSat	LilCv	JBSat	JBCv	Result
1.00	0.02	0.10	0.01	238.66	5.98	(Use nonparametric analysis)'
1.00	0.02	0.21	0.01	593.93	5.98	(Use nonparametric analysis)'
1.00	0.02	0.18	0.01	616.58	5.98	(Use nonparametric analysis)'
1.00	0.02	0.12	0.01	138.22	5.98	(Use nonparametric analysis)'
1.00	0.02	0.10	0.01	94.38	5.98	(Use nonparametric analysis)'
1.00	0.02	0.11	0.01	103.21	5.98	(Use nonparametric analysis)'
1.00	0.02	0.23	0.01	667.19	5.98	(Use nonparametric analysis)'
1.00	0.02	0.16	0.01	9.17	5.98	(Use nonparametric analysis)'
1.00	0.02	0.17	0.01	409.05	5.98	(Use nonparametric analysis)'
1.00	0.02	0.24	0.01	507.74	5.98	(Use nonparametric analysis)'
1.00	0.02	0.16	0.01	660.62	5.98	(Use nonparametric analysis)'
1.00	0.02	0.19	0.01	659.39	5.98	(Use nonparametric analysis)'
1.00	0.02	0.14	0.01	916.71	5.98	(Use nonparametric analysis)'
0.58	0.02	0.04	0.01	482.27	5.98	(Use nonparametric analysis)'

5.4 Artificial Neural Network (ANN)

The odour sample data were normalized using auto-scaling technique that removes the outliers to eliminate the dominance of any sensor. The data were analyses using MLP, RBF and PNN ANN techniques. The technique consists of a number of interconnected neurons, which being processed simultaneously. The ANN model training process used 70 percent of the collected data that's being randomly selected. During training the model iterative weights were kept updated and the network being validated after each epoch. After the training, the ANN model was tested using the remaining data. Table 4 shows the training time for the ANN model. The MLP is the fastest with average 11.15 second follow by PNN 16.55 second and RBF 18.40 second.

Table 4 The ANN model training time

No of Day	MLP(Sec)	RBF(Sec)	PNN (Sec)
1	13	19.03	16.83
2	11.6	17.61	14.49
3	10.8	18.06	16.28
4	9.2	18.9	18.59
Ave	11.15	18.4	16.55

The classification success rate of the ANN model is summarised in Table 5. The classification success rate of the testing for the MLP was 98.22%, while the RBF was 97.81%. The lowest classification success rate of the testing was 83.73% for the PNN. It shows that the instrument classification performance was good and the MLP network model performance was better than that of the RBF and PNN.

Table 5 The testing success rate (%)

No of Day	MLP	RBF	PNN
1	97.97	97.58	84.51
2	98.12	97.8	84.82
3	98.33	98.00	83.61
4	98.47	97.87	81.96
Ave	98.22	97.81	83.73

6.0 CONCLUSION

The research presented in this paper has demonstrated the feasibility of implementing the e-nose to monitor the rubber factory malodour using ANN. The Static headspace method has been employed for sampling the odour sample. The data were pre-processed using the baseline manipulation. The normality test was used to identify the data pattern for suitable classification technique. Then the non-normal data distributions were train using the ANN (MLP, PNN and RBF) for the classification model. The models were able to classify the rubber factory odour samples with good classification success rate. This finding is valuable as it proved the feasibility of using the instrument to monitor the rubber factory malodour. The system can be used to monitor the pollution that will control the impact on humans and the environment. The instruments' data processing can be testing using other pattern recognition techniques such as Support Vector Machine (SVM), K-Nearest Neighbor or Fuzzy ARTMAP which may improve its performance.

Acknowledgement

This project is partly funded by the Malaysian Ministry of Higher Education Research Grant Scheme. A.H. Abdullah also gratefully acknowledges his employer Universiti Malaysia Perlis (UniMAP) for the opportunities given to conduct the research.

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