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# Sensor Array Optimization for Mobile Electronic Nose: Wavelet Transform and Filter Based Feature Selection Approach

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**Abstract** –*Mobile Electronic Nose (MoLen) is a prospective concept for Sensing as a Service ($S^2aaS$) development. Furthermore, gas sensor array is a substantial part of MoLen. This work treats about two issues related with gas sensor array. First, commonly used resistive sensor e.g. MOS (Metal-Oxide Semiconductor) gas sensor is highly contaminated with noise. Second, a poor combination of sensor array leads to features redundancy issue. These problems cause significant performance degradation on classifier. It will get worse if the classifier runs on $S^2aaS$ environment. To deal with these issues, this study proposes the robust sensor array optimization method based on Wavelet Transform to handle the noise and the modified Fast Correlation-Based Filter (FCBF) to find the best combination of sensor array with minimizing feature redundancy. This study has the following contribution: i) reducing the noise from gas sensor array that generated irrelevant data; ii) finding the best sensor array for beef quality classification to improve the quality of input to classifier. The experimental results show that the proposed method successfully reduces the noise power at maximum 14.41% and it is able to determine the best combination of sensors in sensor array with the 16% of improvement of General Resolution Factor (GRF)that is associated with larger classification rate.* 

***Keywords***: *Sensor Array Optimization, Mobile Electronic Nose (MoLen), Feature Selection, Wavelet Transform, Fast Correlation-Based Filter (FCBF)*

## Nomenclature

| | |
|---|---|
| $wt(s,\tau)$ | Wavelet Transform with $s$ scaling and $\tau$ shifting parameters |
| $x(t)$ | Original signal |
| $y(t)$ | Reconstructed signal |
| $T$ | The length of signal |
| $\omega$ | The base wavelet |
| $\overline{a_\iota}$ | Mean of discrete random variable $A$ |
| $\overline{b_\iota}$ | Mean of discrete random variable $B$ |
| $SU(A,B)$ | Symmetrical Uncertainty between $A$ and $B$ |
| $IG(A\|B)$ | Information Gain between $A$ and $B$ |
| $H(A)$ | Entropy value of $A$ |
| $H(B)$ | Entropy value of $B$ |
| $H(A\|B)$ | Entropy of $A$ conditioned on $B$ |
| $P(a_i)$ | Prior probabilities for all values of $A$ |
| $P(a_i\|b_i)$ | Posterior probabilities of $A$ given $B$ values |
| $f_k$ | Feature with index $k$ |
| $S$ | Feature set |
| $SU_{k,c}$ | Symmetrical Uncertainty between feature $k$ and class $C$ |
| $\rho$ | Symmetrical Uncertainty threshold |
| $GRF$ | General Resolution Factor |
| $\mu$ | Mean value of feature |
| $\sigma$ | Standard deviation of feature |
| $m$ | Amount of vectors |
| $Rs$ | Sensor resistance at various concentrations of gases |
| $Vc$ | Circuit Voltage (5V±0.1) |
| $V_{RL}$ | Voltage of sensor in the sample space |
| $RL$ | Sensor load resistance (Ω meter measurement) |
| $ADC$ | ADC values from each sensor |
| $C_{byte}$ | Byte of the microcontroller (1024 byte) |
| $stat$ | Kwiatkowski Phillips Schmidt Shin (KPSS) test |
| $s(i)$ | The vector of residuals from the regression |
| $nw$ | Newey-West estimator of the long-run variance |
| $F_q$ | Sampling frequency |
| $F_{char}$ | Dominant frequency |
| $L$ | Wavelet decomposition level |
| $tp$ | Tuple of feature set |
| $min$ | Time when a particular tuple was generated (in minute) |
| $k$ | The number of features/ sensors amount in sensor array |
| $class$ | Class label based on bacterial population |
| $P_{noise}$ | The power of noise |
| $P_{signal}$ | The power of signal |

## I. Introduction

In the last decade, the utilization of electronic nose (e-nose) has been growing in various areas such as food/product quality control, environmental monitoring,


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biomedical analysis, and so on. In food quality control, e-nose is usually used for the classification of food quality such: beef classification [1]–[7], milk quality identification[8], [9], assessment of the tea aroma [10], [11], etc.

The main component of e-nose is the gas sensor array. It is a combination of various gas sensors with different selectivity. The functionality of sensor array is to collect and to detect odor data from test environment.

Commonly in food quality monitoring, Carbon Dioxide ($CO_2$) is the main indicator of food quality [12], [13]. In addition, air pollutants e.g. Hydrogen Sulfide ($H_2S$) and Ammonia ($NH_3$) as results of the protein decomposition are an indicator of bacterial metabolites [14], [15]. In this study, alcohol, hydrogen ($H_2$), LPG, and water vapour ($H_2O$) are also considered as biomarkers of beef spoilage. The challenge is how to find the best suited combination of sensors from several sensors with overlapping selectivity.

For instance, sensor X has the ability to detect $CO_2$ and methane, sensor Y has the ability to detect $H_2$ and $CO_2$, and sensor Z has the ability to detect LPG and $CO_2$. It will raise the question, which is the best sensor for $CO_2$ detection? In the most of e-nose studies, data pre-processing is only focused to reduce the dimension of multivariate data from sensor array and it commonly employs a feature extraction technique e.g. Principal Component Analysis (PCA)[2]–[7], [16]. PCA generates new variables (Principal Components) from multivariate data which become the input to the classifier without considering the contribution of each feature/variable. The problems related to redundant features and irrelevant data are ignored because the main goal is to reduce the data dimension instead of performing a selection of appropriate features and reduction of irrelevant data.

According to the above explanation, the motivations of this study include:

1) The combination of the used gas sensor has two problems: first, they generate noisy signals that generate irrelevant data and secondly, several sensors yield redundant feature. Typically, the resistive sensor has several types of noises such: thermo-noise, Schottky noise, flicker noise. In the worst case, the signal can contain up to 20% of noise power [17].The redundant feature is usually caused by a poor combination of gas sensors in the sensor array. If these problems cannot be handled properly, they will lead to the performance degradation of classifier, the computation time will be increased and the accuracy will be declined. In the Mobile Electronic Nose (MoLen), the computational time becomes an important aspect in addition to the accuracy [18]. In another study, how long the training will be conducted for the new sample is an important consideration too [6].
2) Furthermore, an excessive number of sensors with overlapping selectivity will lead to a waste of electrical power and to enlarge the size of the data being exchanged on the network.

In addition, several studies also concentrated on the sensor array optimization problems with employing several popular techniques such as using statistic and heuristic model [19], [20], a Rough Set-Based approach[21], Neural Network[22], combination of feature selection methods (t-statistic, MRMR, Fisher Criterion) [23], etc. Another work also addressed an issue about the most significant EEG channel for Fatigue-Driver Detection [24].However, these previous works only addressed how to solve sensor selection problem without considering how to reduce irrelevant data from noisy signal. Even though, the noise ignorance might produce false optimum sensor array.

This paper proposes a robust sensor array optimization method which focuses on two problems: first, irrelevant data reduction is caused by noise; second, redundant features elimination is caused by high correlation among features. Raw signals are obtained by 11sensors to detect gases produced by the beef spoilage.

The wavelet transform is employed to reduce the irrelevant data from non-stationary raw signals. Filter-Based Feature selection technique issued to overcome the problem of feature redundancy caused by high correlated features.

By the selected feature, it is possible to find the most optimal combination of gas sensor array.

There are several common models of feature selection such as Filter, Wrapper, and Embedded. Filter model promises some advantages e.g. models feature dependencies, independent of the classifier, and abetter computational complexity [25], and robustness to solve the overfitting problem [26]. Fast Correlation-Based Filter (FCBF) used in this work is an information-theoretic feature selection method. It was reported for good performance to reduce a large number of features and to increase the classification accuracy [27].

The rest of this paper is arranged into the following sections: Section II deals with related works such as sensor array optimization problems, feature selection, and signal processing. Section III describes the steps that will be performed in this study including signal processing, cluster analysis, feature selection technique, and evaluation. Section IV describes the results of the experiments that have been carried out. Section V is the conclusion of this work.

## II. Related Works

Several feature selection techniques were employed such as a rough set-based approach, reported to find the optimum sensor set for tea classification [10].

Some dry tea samples were used in the experiment to avoid the effect of humidity. Then, eight gas sensors were used to detect the tea aroma from different samples. This approach worked to determine the four best sensors for the classification of black tea.

The evaluation showed that the optimized sensor array just gave an improvement of the 3% of the separability index. In addition, the improvement of classification accuracy based on Back Propagation Multilayer Perceptron (BPMLP) presented an higher accuracy of 11% than byusing an original sensor array.

The combination of three feature selection techniques was reported in [23].This work used eight gas sensors to classify the quality black tea samples. One of the aims was to improve the classification accuracy. It used t-score, fisher’s criterion, and minimum redundancy maximum relevance (MRMR) to construct ranking table of features. SVM as classifier technique was employed to evaluate the performances of the first two features of each individual ranking of three feature selection techniques. However, this paper did not explain why the authors did not perform further analysis of others sensor array combination based on feature ranking. So, the final result was three sensors selected by the first two features of each individual ranking with 6-10% of classification accuracy improvement. Although this paper briefly discussed about the noise contained in the sensor signal, the noise handling was not covered.

In another work, Fast Fourier Transform (FFT) was reported to avoid redundancy in the selected features for electroencephalography signal. Although it presented an average accuracy up to 80% for the emotion detection how to deal with noise were not discussed [28].

Stochastic techniques to select the most optimum sensor array also has been reported [20]. This approach employed genetics algorithm (GA) to improve diversity and to remove redundant sensors. Cluster analysis was also employed to find the amount of sensor groups.

The fitness function of GA is to quantify the maximum distance among sensors. General Resolution Factor (GRF) was proposed to evaluate the quality of input features. In a second paper, the same authors proposed the multi-objective optimization of sensor array. Their objectives were the selectivity and diversity [19]. The selectivity is related with wide range of vapor that can be detected by sensors, while the diversity is related with the capability of sensor array to identify different vapors.However, these objectives were not used simultaneously in the same application.

Another study of sensor array optimization used 15 gas sensors to detect wound infection [29]. It combined genetic algorithm (GA) and quantum-behaved particle swarm optimization (QPSO) to construct synchronous optimization between sensors and classifier. This study proposed the weight of sensor as a degree of importance in classification. Conventional weighting method gives 0 and 1 to mark out the contribution of sensors. If sensor weight is 0, it means there is no contribution. Conversely, 1 means sensor has full contribution. Instead of using traditional weighting method, this study used real number for weighting coefficient. It is called importance factor/ I-F. Some experimental results exhibited that I-F method has a better performance than no-weighting method (using all of sensors).

Using SVM as classifier, optimized sensor array based on I-F method had an improvement of accuracy equal to 7.5%.In addition, the conventional weighting based on GA-QPSO generated a lower accuracy of 12.5% than by using no-weighting method. Although this approach could improve the performance of classifier, sensor array still had 15 online gas sensors because each of them still had weighting coefficient.

It means that the optimization result cannot solve overlapping selectivity, energy saving, and data traffic reduction issues. Sub-arrays is based on sensor array optimization method that performed an exhaustive analysis of sensor selectivity[30].This proposed method focused on sensing material searching and preparation associated with specific sorts of gas. Hierarchical cluster analysis under Euclidean distance was used to construct sub-arrays. In addition, this study attempted to solve the overlapping gas selectivity in two or more sensors. Fisher Discriminant Analysis (FDA) used to the best sub-array means that the smallest sub-array can solve all the gas recognitions.

An unusual approach using neural network sensitivity analysis was proposed in [22]. The sensitivity value was obtained by differential coefficients of the series of neural network outputs and sensors responses. This work tried to reduce gas sensors to a total of six. The first step, was the training and the analysis by using a total of six sensors tested on different neural network configurations (such as: different amount of layers and different amount of neurons). Then, one sensor will be removed based on the sensitivity matrix.

The second step consisted in training the neural network with five sensors data set and to repeat the procedure to reduce the amount of sensors.

The step will end if the response value of the reduced sensor array has significant quality differences respect to the original sensor array. In the conclusion, authors explained the problems of their approach. The first problem is related with the requirement on similar range of the numbers appearing in all the inputs. The second problem is related with the confusing result of the analysis when the inputs are dependent (sensors have overlapping selectivity).

Actually, sensor array optimization is highly associated with feature selection techniques to solve the best feature subset in accordance with sensor array combination. Currently, feature selection has an important role in bioinformatics areas such as microarray and spectral analysis [25].There are several motivations for the use of feature selection: increasing the speed of algorithm, minimizing the computation resources (e.g. memory, storage, and processor), obtaining an higher classification accuracy, and simplifying the data visualization [31].

Feature selection techniques such as Filter, Wrapper, and Embedded are widely used to find the optimal subset of relevant features. Moreover, filter technique is a promising approach to solve the overfitting problem in classification because of its robustness [26], [32].

The overfitting problem creates confusion and frustration to ensure the correct classification results.

Commonly, the main concept of filter technique is the elimination of redundant features by quantifying the correlation among features. An information-theoretic based feature selection is a reasonable choice to measure linear or nonlinear relationship among features in each step of the selection. Mutual Information (MI) or Information Gain (IG) is statistical independence measure to quantify the relationship between two features. The normalized version of MI is Symmetrical Uncertainty. This study employs the Fast Correlation-Based Filter algorithm that uses Symmetrical Uncertainty to determine the gas sensor members in a sensor array.

In another study, all tested filter-based feature selection methods run into performance degradation when the level of noise increases. In the classification problem, the presence of noise leads to the wrong class output [26]. In fact, resistive sensors that are commonly used in e-nose, generate signals contaminated with noise.

In severe condition, the signal of gas sensor can contain up to 20% of noise power [17].

To deal with this problem, wavelet transform is an excellent technique for the time-frequency resolution and the reconstruction of non-stationary signals. Many related works about signal processing using wavelet transform have been reported.

In electroencephalography (EEG) signal processing, the noise is produced by the muscular activity and the eye blinking in addition to the electrical noise. Symlet 9 is the most suitable mother wavelet for EEG signal during working memory task[33], [34].In another work, Electrocardiogram (ECG) signals are corrupted by White Gaussian Noise. Daubechies wavelet of order 9 exhibits the best-suited wavelet for ECG signal de-noising based on MSE and SNR[35].

## III. Proposed Method

The main purpose of this study is to propose a sensor array optimization method based on two aspects: minimizing the irrelevant data caused by the noise and avoiding the data redundancy caused by high correlated features. The schematic sensor array optimization proposed in this study can be seen in Fig. 1.

### *III.1. Signal Processing*

The main purpose of this phase is to perform denoising and compressing signals. The reconstructed signal by this process must be free of noise and compressed properly without losing the essential information. The resistive sensor like MOS (Metal-Oxide Semiconductor) that was used in this work has several types of noise such as thermo noise, shot noise, and flicker noise [17]. Based on this condition, it requires a signal processing technique in accordance with the characteristics and the conditions of the signals.

This study performs Wavelet Transform for the electronic nose non-stationary signals. Wavelet Transform is an excellent technique for non-stationary signal analysis.

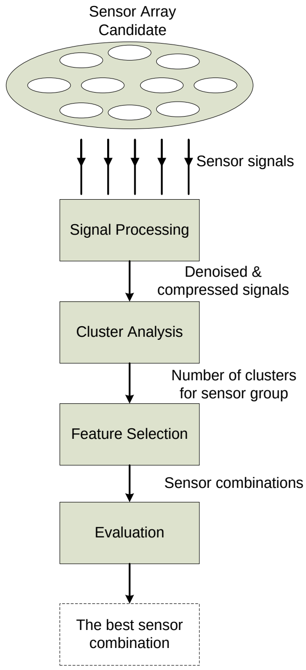



Fig. 1. Proposed sensor array optimization method

Actually, it provides both time and frequency resolution for particular signal in many real-world applications. Commonly, the wavelet transform is used to omit noise from signal and often it is combined with another technique to obtain a satisfactory result. In particular it is combined with filtering and cross-correlation to denoise the raw sensor signal and to locate the gas leak in steel pipe with an error rate less than 3% [10]. Wavelet packet is employed for denoising the spectral signal also reported [31]. Moreover, wavelet packet transform has succeeded to remove the pulse interference in welding quality monitoring [33]. The wavelet transform of a signal $x(t)$ can be expressed in the following way:

$$wt(s,\tau) = \langle x, \omega_{s,\tau} \rangle = \frac{1}{\sqrt{s}} \int_{-\infty}^{\infty} x(t)\omega^*\left(\frac{t-\tau}{s}\right) dt \quad (1)$$

where the symbol $s$ represents the scaling parameter of the base wavelet $\omega\left(\frac{t-\tau}{s}\right)$ and $\omega^*(\cdot)$ denotes the complex conjugation of the base wavelet; $\tau$ is a parameter that translates the wavelet shifting the time axis and $\omega$ describes the used base wavelet. There are several types of mother wavelet that can be used such as haar, daubechies, coiflet, symlet, biorthogonal and reverse biorthogonal, and meyer wavelet.

### *III.2. Cluster Analysis*

The number of clusters is needed to determine the maximum number of features in the feature selection algorithm. Sensors will be grouped into several sub-arrays based on their selectivity. The number of clusters is associated with the optimal amount of gas sensors in the sensor array. This study employs the hierarchical clustering to find the number of clusters based on data similarity. Centroid clustering with Euclidean distance is used for its better handling of outlier data based on its comparison with the hierarchical cluster analysis methods [36].

### *III.3. Feature Selection*

Commonly, the purpose of the feature selection is to determine the best combination of features by removing a number of features. In this work, feature selection aims to find the best gas sensor combination based on the gases produced by the spoilage of beef. Some relevant features can be found by looking for the correlation among features with class label. On the other hand, a high correlation among features would lead to a feature redundancy. The common correlation coefficient was used by another work to build the signals correlation matrix among 8 sensors [7]. It can be expressed by the following equation:

$$Coef(A,B) = \frac{\sum_{i=1}(a_i - \overline{a_i})(b_i - \overline{b_i})}{\sqrt{\sum_{i=1}(a_i - \overline{a_i})^2}\sqrt{\sum_{i=1}(b_i - \overline{b_i})^2}} \quad (2)$$

where $\overline{a_i}$ is mean of $A$ and $\overline{b_i}$ is mean of $B$. Unfortunately the function of the correlation matrix for sensor array optimization was not visible. Moreover, Pearson correlation coefficient is only sensitive to the linear relationship between two variables. Naturally, the relationship between two variables is often nonlinear. So, assuming that any relationship between the two variables is linear, is not a safe assumption. It is required another approach to seek the nonlinear correlation coefficient of two variables. This work employs Fast Correlation-Based Filter (FCBF) to find the best-suited features. FCBF uses the entropy-based correlation coefficient, called Symmetrical Uncertainty (SU), as follows:

$$SU(A,B) = 2\left[\frac{IG(A|B)}{H(A)+H(B)}\right] \quad (3)$$

where:

$$IG(A|B) = H(A) - H(A|B) \quad (4)$$

$$H(A) = -\sum_{i=1} P(a_i)log_2(P(a_i)) \quad (5)$$

$$H(B) = -\sum_{i=1} P(b_i)log_2(P(b_i)) \quad (6)$$

$$H(A|B) = -\sum_{j=1} P(b_j)\sum_{i=1} P(a_i|b_i) \\ log_2(P(a_i|b_i)) \quad (7)$$

SU value has a range from 0 to 1. If the value is equal to 1 then the value of a variable will be able to fully predict the value of the other variables. Conversely, if the value is 0, then the two variables are independent. $P(a_i)$ is the prior probability for all the values of $A$ and $P(a_i|b_i)$ is the posterior probability of $A$ given $B$ values.

FCBF has two important steps named C-Correlation and F-Correlation. C-Correlation is a relationship between feature $f_k$ and class $C$ while the F-Correlation is the pairwise correlation among the entire features.

The value of relationship is represented by SU. In the original FCBF algorithm, the search strategy to avoid the feature redundancy is based on the predominant correlation and the predominant feature.

A correlation is called predominant correlation when the correlation between feature $f_k(f_k \in S)$ and class $C$ fulfills the conditions in which $SU_{k,c} \geq \rho$ and $\forall f_l \in S$, $(k \neq l)$ nothing $SU_{l,k} \geq SU_{k,c}$, ($\rho$ = *threshold*), while the predominant feature starts the search from the feature with the biggest $SU_{k,c}$. The searching strategy of original FCBF feature selection is like a greedy search where the search will be fully referred to the predominant feature.

This leads to the neglect of other features. This study tries to adopt some modified different search strategies which were proposed by another work [37].

This searching strategy uses the concept of temporary predominant feature of the selection process. So, it becomes more balanced and every feature has a chance of being selected. This is very useful if we need to find the $k$ number of feature subset.

The $k$ number is determined by the cluster group generated in the cluster analysis step. In this work, the threshold value has been set not lower than 0.1 to eliminate the possibility that features with very low C-Correlation will be selected. The strategy to perform the feature selection can be seen in Algorithm 1.

**Algorithm 1. Modified FCBF Algorithm**

```
threshold ← 0.1 /* set SU minimum threshold */
max_feature ← 11 /* the amount of the total features */

/* Generating Symmetrical Uncertainty Matrix (SUM) */
for i : 1 to max_feature+1 do
for j : 1 max_feature+1 do
temp ← calcSU(fi,fj)
if (temp ≤ threshold) then
temp ← 0
end if
SU(i,j) ← temp
end for
end for

/* Ranking the features */
c_corr ← sort(c_correlation, 'descending')

k ← 7 /* setting the amount of the expected features */
feature ← max_feature

/* Determining the best k features */
i ← 1;
while (i ≤ max_feature-1)&&(feature ≠ k) do
j ← 1;
while (j ≤ max_feature-1) do
        if (SU[i,max_feature+1-j] ≥
        c_corr[max_feature+1-j]) then
setInvalid(c_corr[max_feature+1-j])
feature ← feature-1
if(feature = k) then
break
end if
end if
j ← j+1
end while
i ← i+1
end while
```

### III.4. Evaluation

Several criteria have been proposed for the sensor array optimization in the past literature such as the classification rate [7], [22], the distance measure [19],[20], and the comparison between classification rate and distance measure [10].

Considering that the classification rate does not only depend on the quality of input features but also by the parameter setting and the environment configuration, the evaluation result is produced by employing a classifier that does not guarantee the quality of the input features.

So, a high correct classification rate can mean overfitting. According to the above explanation, it will be necessary to verify the quality of the input features before they are consumed by another process.

This work uses General Resolution Factor (GRF)to measure the input quality of the selected features [20]. GRF can be expressed by the following equation:

$$GRF = \sqrt{\sum_{i=1}^{m} \frac{(\mu_{i1} - \mu_{i2})^2}{{\sigma_{i1}}^2 + {\sigma_{i2}}^2}} \tag{8}$$

Assuming Gaussian distribution, the larger ratio between centroid distance ($\sqrt{\mu_{i1} - \mu_{i2}}$) and $\sqrt{{\sigma_{i1}}^2 + {\sigma_{i2}}^2}$is related with a larger probability of correct classification rate[38].

## IV. Result and Discussion

Mobile Electronic Nose (MoLen) sensor box prototype is built based on the Arduino platform.

MoLen sensor box is designed to test the gases from a beef sample. The meat sample used for the experiment is a 500g fresh beef that was observed for approximately three days. The data taken from the 11 sensors are transmitted by the MoLen sensor box to the server every minute during 4720 minutes (78.67 hours).

Time series data derived by the observations of the beef spoilage were obtained at ±38°C and 75% of humidity. This condition was selected to accelerate the growth of mesophilic bacteria.

### IV.1. MoLen Sensor Box Setup

The used MoLen sensor box is customized to the needs of Sensing as a Service ($S^2$aaS) environment. Built on the Arduino Platform with 10 analog gas sensors and a digital temperature-humidity sensor, MoLenis is equipped with a wifi shield as wireless communication interface for the online data acquisition. So, it is an improvement of conventional e-nose used in previous studies that acquired the data offline. The Molen sensor box can be seen in Fig. 2. For the data acquisition, the signal from the sensor array is sent via wireless network through an additional wifi shield on the arduino board.

The composition of the sensor array can be seen in Table I. All gas sensors in Table I are resistive sensors (Metal-Oxide Semiconductor/MOS), except DHT22. In addition, gas sensor is an analog sensor so the output data are the result of analog to digital conversion (ADC).


Fig. 2. MoLen Sensor Box: (1) Gas sensor array; (2) Sample chamber; (3) Arduino microcontroller and Wifi-Shield

TABLE I
GAS SENSOR LIST

| No | Sensor | Selectivity |
|---|---|---|
| 1 | MQ135 | $NH_3$ (Ammonia), $NO_x$, alcohol, Benzene, smoke, $CO_2$ |
| 2 | MQ136 | Hydrogen Sulfide ($H_2S$) |
| 3 | MQ2 | LPG, i-butane, propane, methane, alcohol, Hydrogen, smoke |
| 4 | MQ3 | Alcohol, Benzene, Methane ($CH_4$), Hexane, LPG, CO |
| 5 | MQ4 | Methane ($CH_4$),Natural gas |
| 6 | MQ5 | LPG, natural gas , town gas |
| 7 | MQ6 | LPG, iso-butane, propane |
| 8 | MQ7 | Carbon Monoxide (CO) |
| 9 | MQ8 | Hydrogen ($H_2$) |
| 10 | MQ9 | Methane, Propane and CO |
| 11 | DHT22 | Temperature & Humidity |

The ADC value must be converted to obtain the resistance (*Rs*) value of the sensor:

$$Rs_i = \frac{V_c - V_{RL_i}}{V_{RL_i} \cdot RL_i} \tag{9}$$

$$V_{RL_i} = \frac{ADC_i \cdot V_c}{C_{byte}} \tag{10}$$

*Rs* : sensor resistance at various concentrations;
*i* :number of sensors;
*Vc* : Circuit Voltage (5V±0.1);
$V_{RL}$ : Voltage sensor in the sample space;
*RL* : Sensor load resistance (Ω meter measurement);
*ADC* : ADC values from each sensor;
$C_{byte}$ : Byte of the used board(1024 byte).

### IV.2. Signal Processing

It is very important to ensure that the noisy signal has been processed properly. Denoising and compressing are essential processes because they can guarantee that the next process will consume valid data.

Identifying the signal characteristic is an important step before conducting the signal processing because it will determine the most appropriate signal processing technique. Fig. 3 shows a signal sample of one of the gas sensors. The signal can be broadly classified as deterministic and non-deterministic signal [39]. The deterministic signal is a signal that can be expressed mathematically and viceversa. The signal sample of a gas sensor in Fig. 3was tested to determine the characteristic of the signal.

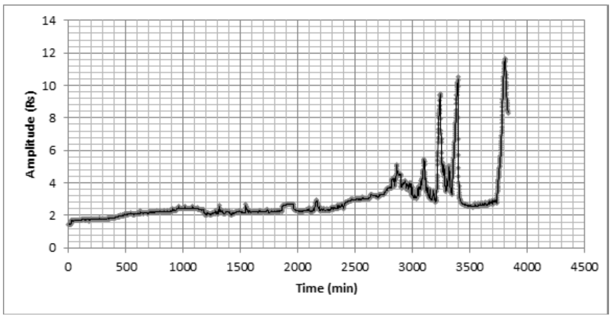



Fig. 3. A signal sample of a gas sensor

Visually, this signal can be easily identified as random signal (non-deterministic). Mathematically, it is very difficult to express a sample of a signal.

Nevertheless, this research tried to define the mathematical function of a sample of the signal. Fig. 4 shows several mathematical function approaches and $R^2$ values using MS Excel for the sample of signal. It shows that the exponential function is the most appropriate mathematical function based on the highest$R^2$value.

However, it is not very safe to assume that the signal can be expressed in a mathematical function with maximum $R^2$= 0.5747. Moreover, it does not guarantee that the value of $R^2$will be constant or it will increase for the next time series so the non-deterministic signal is the most reasonable for this signal characteristics.

Furthermore, non-deterministic signal can be generally divided into two categories (stationary and non-stationary). So, an additional test is needed to affirm for non-deterministic signal and to determine whether the signal is stationary or non-stationary.

Kwiatkowski Phillips Schmidt Shin (KPSS) tests are used for testing the null hypothesis that an observable time series is stationary around a deterministic trend; it can be expressed by the following equation [40]:

$$stat = \sum_{i=1}^{T} \frac{s(i)^2}{{s_{nw}}^2 T^2} \tag{11}$$

KPSS test is needed also to prove one of these two hypothesis: $H_0$: The series is stationary or $H_a$: The series is non-stationary. The stationary test shows that all signals are non-stationary with the risk to reject the stationary signal hypothesis equal to less than 0.01%.

Discrete Wavelet Transform (DWT) is used to perform the denoising and compressing signal from the sensor array. The main parameters of DWT can be seen in Table II. Signal numbers 1,2,…,11 correspond to sensors 1,2,...,11 respectively. The decomposition level is determined by the dominant frequency using the following rule:

$$\frac{F_q}{2^{L+1}} \leq F_{char} \leq \frac{F_q}{2^L} \tag{12}$$

where $F_q$ is the sampling frequency, $F_{char}$ is the dominant frequency, and $L$ is the decomposition level.

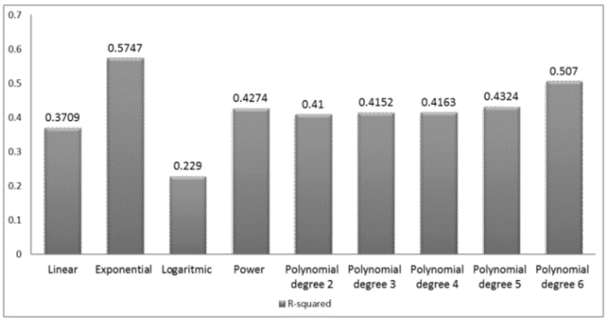



Fig. 4. Various $R^2$ value of mathematical functions

TABLE II
DWT PARAMETERS

| Signal | MaxFrequency (Hz) | Decomposition Level | Mother Wavelet |
|---|---|---|---|
| 1 | 0.43 | 11 | bior2.4 |
| 2 | 0.43 | 11 | bior3.3 |
| 3 | 0.43 | 11 | db1 |
| 4 | 0.65 | 10 | bior3.3 |
| 5 | 0.65 | 10 | db1 |
| 6 | 0.87 | 10 | sym6 |
| 7 | 0.43 | 11 | bior2.2 |
| 8 | 1.30 | 9 | - |
| 9 | 0.65 | 10 | dmey |
| 10 | 0.65 | 10 | db1 |
| 11 | 0.65 | 10 | db6 |

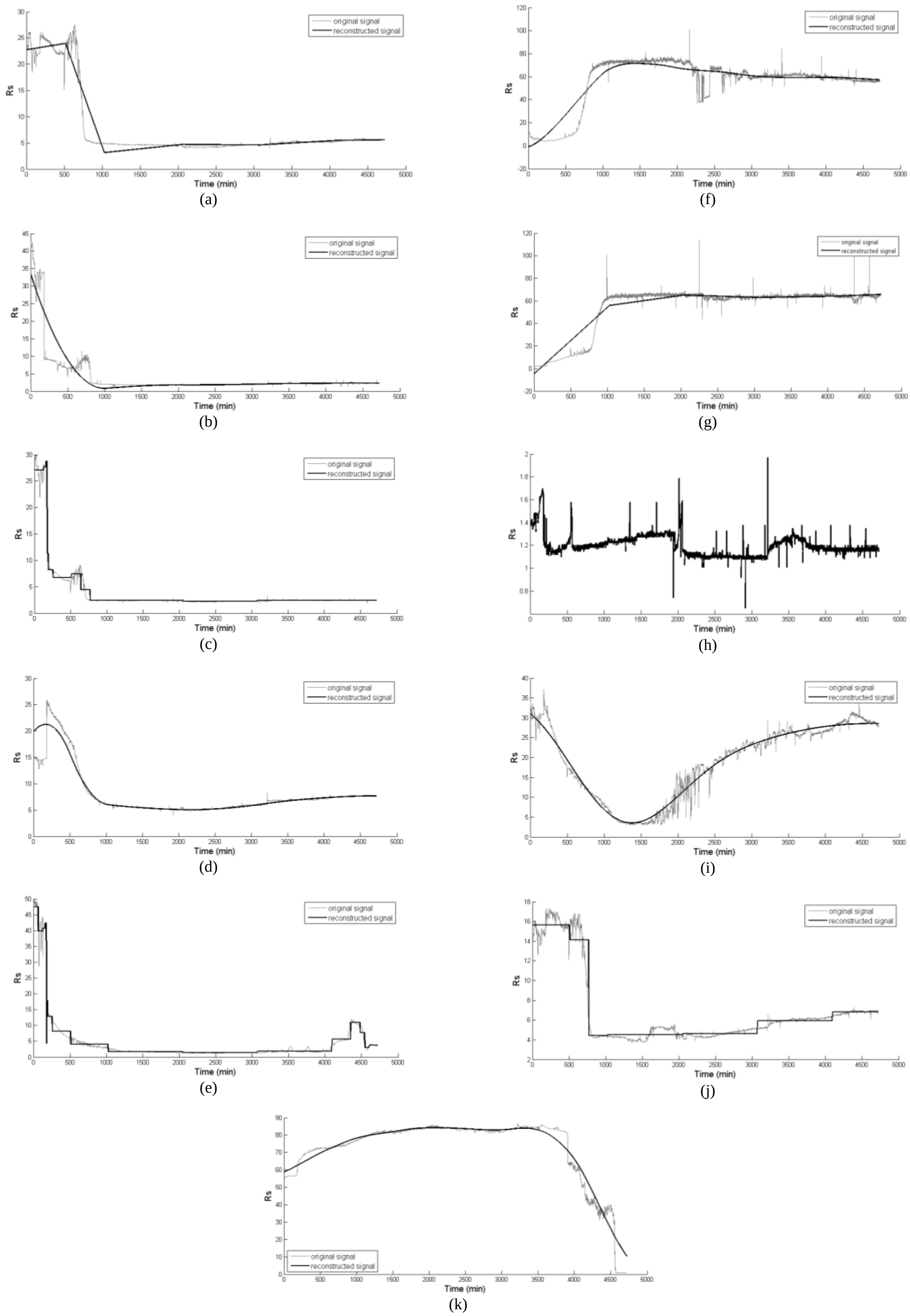
The mother wavelet is determined by calculating the relationship between the original signal and the reconstructed signal. The maximum ratio between mutual information and joint entropy is used to measure this relationship and to find the best-suited mother wavelet for particular signal.

All signals can be reconstructed by a particular mother wavelet except the signal 8 because the mutual information value is equal to zero for all the tested mother wavelets. So, it is necessary to keep this original signal for the next process.

The comparison between the original and reconstructed signals is demonstrated in Figs. 5.

The performance measurement of the wavelet transform for the signal denoising can be calculated by the reduced noise power. It is obtained by the total squared difference between the original and the reconstructed signal, then it is divided by the length of signal. Mathematically, it can be expressed by the following equation:

$$P_{noise} = \frac{1}{T} \sum\nolimits_{t=1}^{T} |x(t) - y(t)|^2 \tag{13}$$




(a) (f) (b) (g) (c) (h) (d) (i) (e) (j) (k)

Figs. 5. Originals (red) and reconstructed (black) signals: signal 1 (a), signal 2 (b), signal 3 (c), signal 4 (d), signal 5 (e), signal 6 (f) signal 7 (g), signal 8 (h), signal 9 (i), signal 10 (j), signal 11 (k)

$$P_{signal} = \frac{1}{T}\sum_{t=1}^{T} |y(t)|^2 \quad (14)$$

where $x(t)$and $y(t)$are the original and thereconstructed signal respectively. $T$ is the length of signal. Table III demonstrates the reduction of noise by the wavelet transform. According to Table III, the wavelet transform denoising can reduce the noise power against the signal power to a maximum of 14.41% and an average of 2.46%.

### *IV.3. Cluster Analysis*

The cluster analysis aims to make an estimation of the amount of gas sensors on the sensor array. Cutting the dendrogram at the middle level of dissimilarity (1900), it can be seen in Fig 6 that the sensors can be roughly divided into 3 sensors group, 4 sensors group, 5sensors group, 7 sensors group, or 8 sensors group.

The next question is how to determine the member of each group. In this issue, the feature selection technique is needed to find the best *k* members in each group.

TABLE III
SIGNAL AND NOISE POWER

| Signal | $P_{signal}$ | $P_{noise}$ | Percentage of reduced noise (%) |
|---|---|---|---|
| 1 | 101.28 | 2.68 | 2.65 |
| 2 | 51.90 | 7.48 | 14.41 |
| 3 | 38.38 | 0.40 | 1.04 |
| 4 | 83.27 | 2.12 | 2.54 |
| 5 | 86.15 | 1.08 | 1.25 |
| 6 | 3420.88 | 66.84 | 1.95 |
| 7 | 3323.62 | 41.74 | 1.26 |
| 8 | 1.45 | 0.00 | 0.00 |
| 9 | 432.01 | 2.70 | 0.63 |
| 10 | 61.17 | 0.62 | 1.02 |
| 11 | 5552.90 | 19.65 | 0.35 |

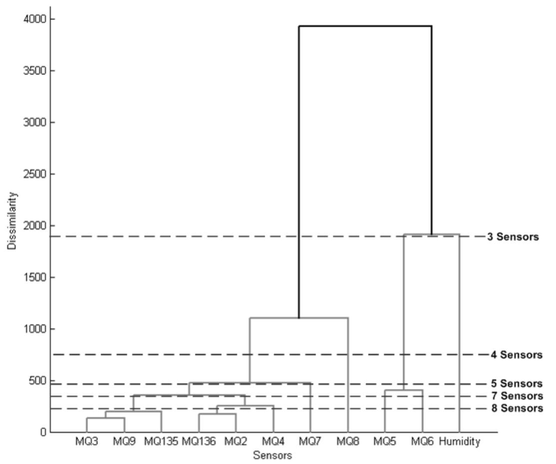



Fig. 6. The amount of sensors in sensor array based on AHC

### *IV.4. Feature Selection*

In this study, the grade of beef is based on the standard issued by Meat Standards Committee of ARMCANZ (Agricultural and Resource Management Council of Australia and New Zealand).

It uses an amount of bacterial cells in cfu/g on meat as shown in Table IV. According to Table IV, beef decay time can be precisely determined. Fig. 7 demonstrates the real bacterial growth in anaerobic environment.

TABLE IV
CLASS OF BEEF QUALITY

| Category | Amount of Bacterial Cells ($\log_{10}$cfu/g*) |
|---|---|
| Excellent | < 3 |
| Good | 3-4 |
| Acceptable | 4-5 |
| Spoiled | >5 |

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

Spectrophotometer (Genesys 20) is used to measure the optical density (600nm) and haemocytometer is used to calculate the number of cells. The experiment adopts classical and two-hour methods [41].

It also demonstrates the history of the meat quality ranging from excellent, good, acceptable, and spoiled.

According to the curve area in Fig. 7 and to the sensor signals, a feature set in the following tuple *tp* has been constructed:

$$tp = \langle min, x_1, x_2, \ldots, x_k, class \rangle \quad (15)$$

where *min* is the time during which a particular tuple is generated (in minute), *x* is the signal from the related gas sensor, *k* is the sensor amount in sensor array, and *class* is the class label based on bacterial population. Based on tuple *tp*, Symmetrical Uncertainty Matrix (SUM) is constructed to find F-Correlation and C-Correlation as shown in Table V.

FCBF algorithm utilizes the SUM to determine the best feature subset in each sensor group.

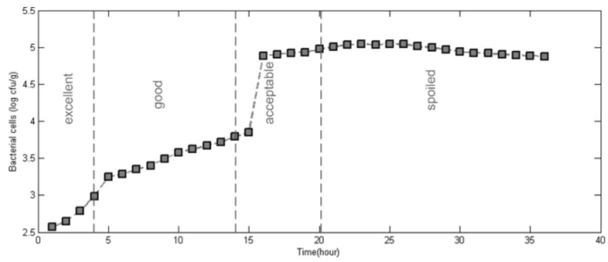


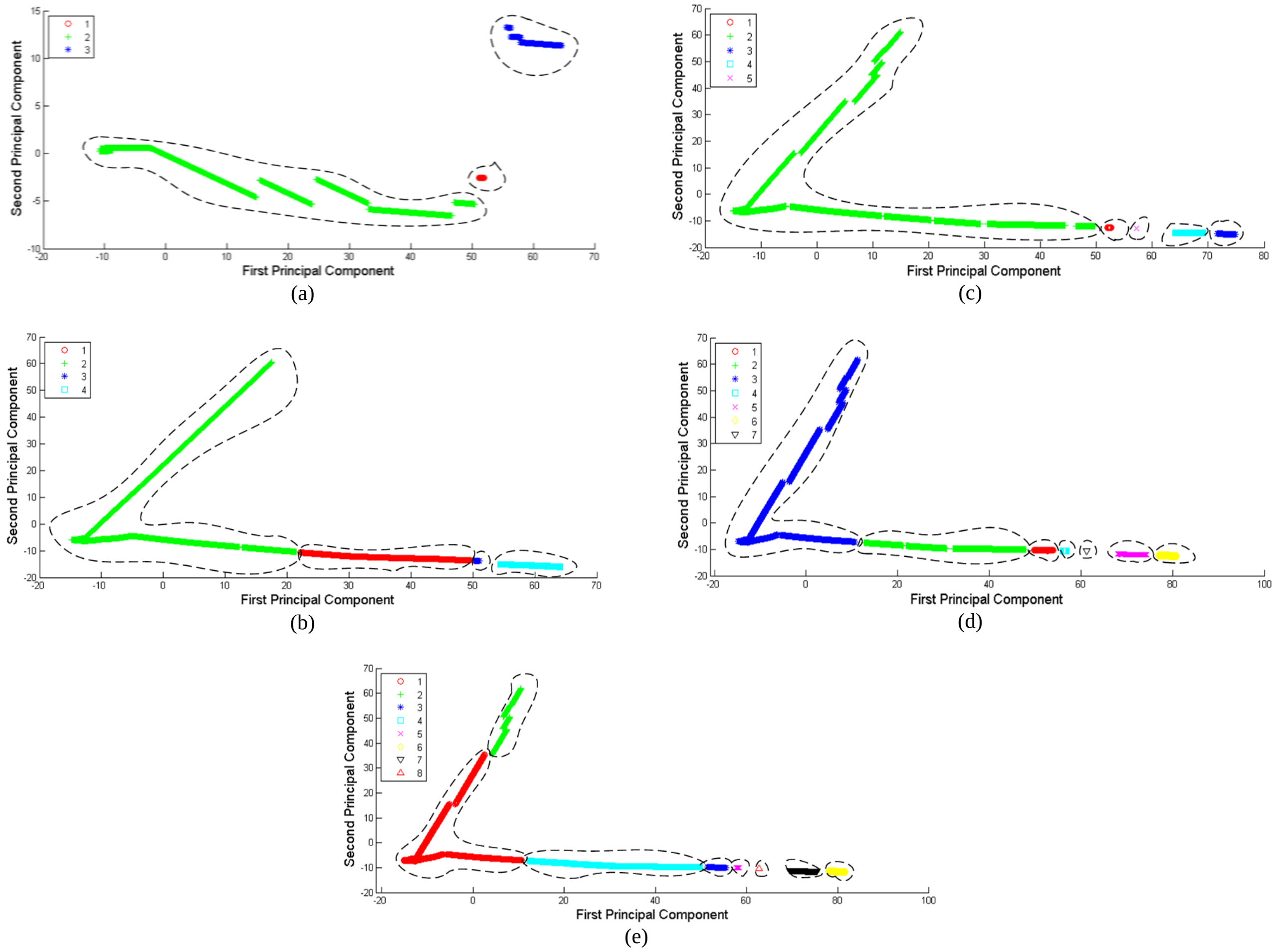

Fig. 7. Bacterial growth and class of beef quality at room temperature

Five groups of sensors (3 sensors group, 4 sensors group, 5 sensors group, 7 sensors group, or 8 sensors group) generated by the cluster analysis are necessary to determine the combination of sensor array members. FCBF is used to find the most optimal combination of sensors for each sensors group.

Optimal combination means to eliminate the irrelevant features and to minimize the redundant features in the final combination result. It is associated with minimizing the amount of sensors and avoiding the overlapping selectivity among sensors in the sensor array. Table VI shows the sensor array members in each group.

TABLE V
SYMMETRICAL UNCERTAINTY MATRIX (SUM)

| | Symmetrical Uncertainty | F-Corr | | | | | | | | | | | C-Corr |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **MQ135** | **MQ136** | **MQ2** | **MQ3** | **MQ4** | **MQ5** | **MQ6** | **MQ7** | **MQ8** | **MQ9** | **DHT22** | **Class** |
| **F-Corr** | **MQ135** | 1.000 | 0.566 | 0.475 | 0.650 | 0.514 | 0.531 | 0.576 | 0.000 | 0.475 | 0.574 | 0.522 | 0.488 |
| | **MQ136** | 0.566 | 1.000 | 0.562 | 0.655 | 0.491 | 0.592 | 0.529 | 0.000 | 0.464 | 0.625 | 0.408 | 0.485 |
| | **MQ2** | 0.475 | 0.562 | 1.000 | 0.511 | 0.576 | 0.356 | 0.398 | 0.000 | 0.192 | 0.531 | 0.279 | 0.636 |
| | **MQ3** | 0.650 | 0.655 | 0.511 | 1.000 | 0.524 | 0.578 | 0.505 | 0.000 | 0.491 | 0.679 | 0.462 | 0.414 |
| | **MQ4** | 0.514 | 0.491 | 0.576 | 0.524 | 1.000 | 0.475 | 0.513 | 0.000 | 0.326 | 0.632 | 0.494 | 0.552 |
| | **MQ5** | 0.531 | 0.592 | 0.356 | 0.578 | 0.475 | 1.000 | 0.687 | 0.000 | 0.686 | 0.519 | 0.563 | 0.319 |
| | **MQ6** | 0.576 | 0.529 | 0.398 | 0.505 | 0.513 | 0.687 | 1.000 | 0.000 | 0.595 | 0.414 | 0.574 | 0.446 |
| | **MQ7** | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 1.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | **MQ8** | 0.475 | 0.464 | 0.192 | 0.491 | 0.326 | 0.686 | 0.595 | 0.000 | 1.000 | 0.441 | 0.543 | 0.176 |
| | **MQ9** | 0.574 | 0.625 | 0.531 | 0.679 | 0.632 | 0.519 | 0.414 | 0.000 | 0.441 | 1.000 | 0.374 | 0.438 |
| | **DHT22** | 0.522 | 0.408 | 0.279 | 0.462 | 0.494 | 0.563 | 0.574 | 0.000 | 0.543 | 0.374 | 1.000 | 0.298 |
| **C-Corr** | **Class** | 0.488 | 0.485 | 0.636 | 0.414 | 0.552 | 0.319 | 0.446 | 0.000 | 0.176 | 0.438 | 0.298 | 1.000 |




Figs.8. PCA plot of sensor group: (a) 3 sensors group (b) 4 sensors group(c) 5 sensors group
(d) 7 sensors group (e) 8 sensors group

### *IV.5. Evaluation*

Each group of sensors must be evaluated to find the best group of sensors. The same amount of the principal components by the Principal Component Analysis in each group containing enough information of the original data is compared. Visually, the input quality of each sensor group is demonstrated by PCA plot in Figs. 8.

Quantitatively, the feature subset quality of each sensor group is compared based on GRF. GRF values are calculated by the first two of the corresponding principal components from each sensor group.

Table VII demonstrates that 7 sensors group has the biggest GRF value than others. So, it could be determined that 7 sensors group is the best sensor array. The utilization of 7 sensors group presents 16% of the quality improvement of the input features than by using all (11) sensors.

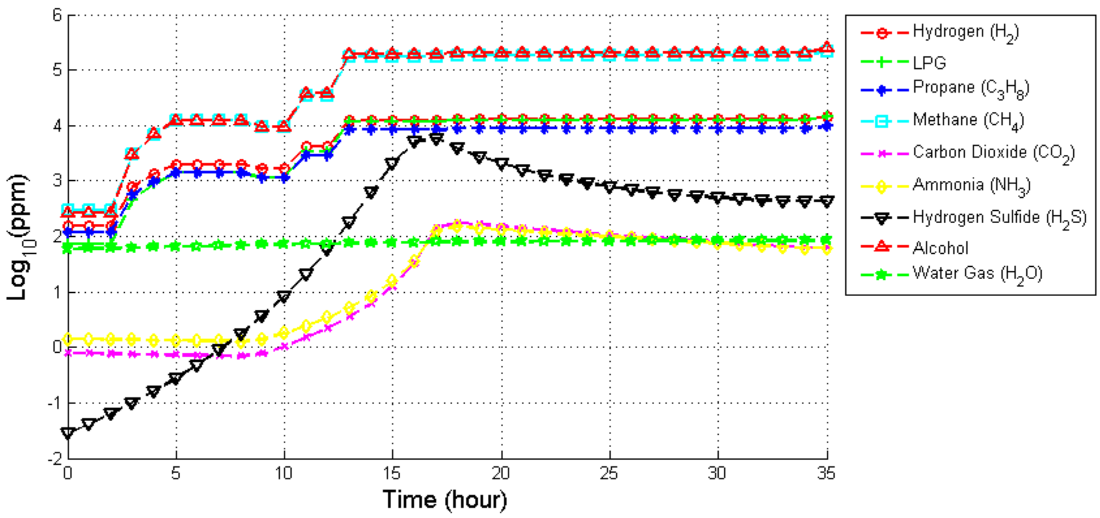



Fig. 9. Various gases concentration ($\log_{10}$(ppm)) in beef spoilage

In addition, it was made also an observation about the concentration of the various gases in the beef spoilage.

This observation is conducted with the following rules:

1) Gas concentration is quantified starting from the sensor with the highest C-Correlation and it continues to the sensor with the lower C-Correlation.
2) Adding selectivity from the next sensor (sensor with lower C-Correlation).
3) If the next sensors have an overlapping selectivity with the previous sensor then the same selectivity will be ignored.
4) Repeating step 2-3 until the sensor with the lowest C-Correlation will be found.

Fig.9 demonstrates the trend of nine types of gases in beef spoilage such as hydrogen ($H_2$), LPG, propane ($C_3H_8$), methane ($CH_4$), carbon dioxide ($CO_2$), ammonia ($NH_3$), hydrogen sulfide ($H_2S$), alcohol, and water vapor.

TABLE VI
MEMBERS OF SENSOR ARRAY

| Sensor Array | Sensor Members |
|---|---|
| 3 Sensors | MQ2,MQ135,MQ6 |
| 4 Sensors | MQ2,MQ135,MQ6, DHT22 |
| 5 Sensors | MQ2,MQ135,MQ6, DHT22,MQ4 |
| 7 Sensors | MQ2,MQ135,MQ6, DHT22,MQ4,MQ136,MQ9 |
| 8 Sensors | MQ2,MQ135,MQ6, DHT22,MQ4,MQ136,MQ9,MQ3 |

TABLE VII
GRF VALUE OF EACH SENSOR ARRAY

| Sensor Array | GRF Value |
|---|---|
| 3 Sensors | 0.09101 |
| 4 Sensors | 0.24844 |
| 5 Sensors | 0.24298 |
| **7 Sensors** | **0.25005** |
| 8 Sensors | 0.24882 |
| All (11) Sensors | 0.21592 |

Methane and alcohol are gases with the highest concentration. They are stagnant in the first three hours and rise significantly after 3 hours of meat storage. The same trend occurred in hydrogen, LPG, and propane with lower concentration. It means that mesophilic bacteria in the lag phases during the first three hours and then grows exponentially. The existence of methane, $CO_2$, $NH_3$, and $H_2S$ is yielded by the protein decomposition. It indicates the quality degradation of the beef.

## V. Conclusion

This method has been successfully reduced the irrelevant data and optimized the sensor array by eliminating the redundant features with the following performances:

1. Wavelet transform successfully reduces the irrelevant data from the noise with an average of 2.46% and maximum of 14.41%of the overall signal power generated by the sensor array, except signal 8 (carbon monoxide sensor) because it does not have a relationship with the beef spoilage, actually.
2. This method has successfully reduced the number of sensors and determined the best combination of sensor array based on the highest GRF value. GRF value of selected sensor array (7 sensors group) has 16% higher respect to the use of 11 sensors though still has an overlapping selectivity. It relates to the possibility of higher correct classification rate. Furthermore, the selectivity of all the selected sensors has a relevance with the gases produced by beef spoilage bacteria. MQ2 is sensitive to methane, alcohol, and hydrogen. MQ135 is sensitive to carbon dioxide and ammonia. MQ6 is sensitive to LPG. DHT22 is sensitive to humidity (water vapor). MQ4 is sensitive to methane. MQ136 is sensitive to hydrogen sulfide. MQ9 is sensitive to methane and propane.

The future works will carry out the beef quality classification using a classifier. Accuracy and computational time are the main parameters.

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