Chapter 4: Best Waveform for Temperature Modulation

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4.0 Introduction

Application of a constant heating voltage to the gas sensor for differentiating multiple odour analytes is a very common practice. But the application of a constant heating voltage provides limited feature set, resulting in weak classification performance of PARC for multiple gas detection [1]. As such temperature modulation of MOS gas sensors are being employed by various researchers which produces better feature set for higher classification performance for multiple gas detection. In temperature modulation, a cyclic heating voltage profile is applied to the heater. The cyclic variation in the working voltage of the gas sensor results in cyclic variation of its operational temperature. The sensor temperature is determined by the amplitude of the voltage applied across the heater. The rate of kinetics of the sensor reaction also follows the heating waveform and provides unique response for each gas. Temperature modulation provides rich set of features that helps in identification of gases [2]. For a particular application of odour detection, all the sensors of the array may not produce equally informative and relevant features. So consideration of optimum sensors in the array is very important. The previous chapter presented the results of sensor optimization. An optimum subset of 4 sensors was determined for enhanced cluster separation and classification.

Another approach to produce better features from thermally modulated gas sensors is the use of an optimum waveform for temperature modulation. Different modulation waveform varies the sensor temperature and corresponding reaction kinetics in its own way resulting in different characteristic response waveforms [3]. Therefore the optimum modulating waveform may be found out which will result in the production of the best and informative signals for a particular odour set and enhance the classification performance of the PARC. In this chapter an approach for determining the best temperature modulation waveform is discussed and results are presented.
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4.1 Literature review

Temperature modulation of MOS gas sensors have been investigated by many researchers with various shapes of the heating waveform. In [4], Nakata et al. applied sinusoidal temperature modulation to SnO$_2$ gas sensors and used the FFT harmonics to the obtained multi dimensional information in order to quantify mixtures of hydrocarbon. In [5], Heilig et al. also used the sinusoidal temperature modulation to analyze a mixture of CO and NO in air. They applied FFT to obtain features from a micromachined sensor array and used those features in a neural network based classifier for classification. In [6], Llobet et al. conducted similar studies with SnO$_2$ sensors for quantifying mixtures of CO and NO$_2$. They used DWT to extract features from the sensor responses. In [7], Cavicchi et al. used a cyclic pulsed heating waveform for temperature modulation of the gas sensors. In [8], Bukowiecki et al. used heating waveforms like triangular, sawtooth, square wave etc. to identify CO, Methane, Ammonia and Hydrogen. In [9], Ngo et al. employed temperature modulation using triangular waveforms and neural networks to identify three gases- CO, acetylene and hydrogen sulphide. In [10], Ding et al. experimented with sinusoidal temperature modulation applied to a single MOS sensor and used wavelet transform to extract features from the thermally modulated sensor’s response for identification of hydrogen, CO and their mixture.

In [11], Vergara et al. presented an approach to optimize the multi sinusoidal signal used for temperature modulation and then found the best frequency to different mixtures of different gases and achieved 100% classification success using FFT extracted features. In [12], Dutta et al. investigated an optimal set of rectangular temperature modulating frequency and duty cycles using system identification theory. The model parameters was estimated using iterative prediction-error minimization (PEM) method and using sensor stability, the best suited transfer function was found out for the MOS gas sensors. In [13], Osuna et al. investigated on a sinusoidal heating profile to analyze the sensor behaviour at
different frequency and concluded that at a lower frequency the response provided more discriminative features. Osuna et al. also studied in [14], a staircase waveform temperature profile on the sensor and found that each step in temperature yielded a characteristic shape. In [15], Chutia et al. investigated on saw-tooth temperature modulation of MOS gas sensors. Features were extracted using wavelet transform and the best frequency of the heating waveform was found out using support vector machine based classifier.

In the previous chapter and an optimum subset of 4 sensors was found out which resulted in best cluster separation. In this chapter the results of study on determining the best heating waveform of MOS gas sensors for discriminating 16 different chemicals is presented.

4.2 Acquisition of odour data

The main objective in the current investigation is to determine the best heating waveform for detection of gases as listed in Table 2.3. In this investigation, we have used the optimized sensor subset of 4 sensors namely TGS826, TGS821, TGS2611 and TGS825 as presented in Chapter 3 for data acquisition. In this research a total of 9 different shapes of temperature modulation waveform were considered for analysing and determining the best waveform. The 9 different temperature modulation waveforms considered were rectangular, sinusoidal, saw-tooth, sigmoid, exponential, triangular, decreasing saw-tooth, decreasing sigmoid and decreasing exponential. The time period of each of these cyclic waveforms were 50 seconds. These waveforms were generated by a microcontroller based waveform generator circuit as discussed in Chapter 2. The odour data was acquired for 16 gases and two concentrations as listed in Table 3.1. The data acquisition was performed at 20 Hz using the developed DAS. This resulted in a 1000 point response waveform during a period of a waveform. Figure 4.1 to 4.9 shows the plot of the response waveforms of gases to various temperature modulation waveforms. Each of the 1000 point
signals were filtered using moving average filter to remove high frequency noise and sub-sampled to 1 Hz for data compression. This resulted in a 50 point signal for each of the waveforms.

Figure 4.1 Plot of I) the rectangular modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte
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Figure 4.2 Plot of I) the sinusoidal modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte
Figure 4.3 Plot of I) the sawtooth modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte
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Figure 4.4 Plot of I) the sigmoid modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte.
Figure 4.5 Plot of I) the exponential modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte
Figure 4.6 Plot of I) the triangular modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte.
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Figure 4.7 Plot of I) the decreasing sawtooth modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte
Figure 4.8 Plot of I) the decreasing sigmoid modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 ul of liquid analyte.
Figure 4.9 Plot of I) the decreasing exponential modulating waveform used as heating voltage and II) the corresponding 50 samples collected from 4 sensors for 16 gases for concentration corresponding to 4 μl of liquid analyte
4.3 Normalization of the signal

As was discussed in Chapter 3 about the necessity of normalization, the 50 point response waveforms were normalized to eliminate the effect of drift of sensors as well the variation due to change in concentration. The same normalization method of dividing each sensor response by the maximum value responded by any of the sensor during a measurement as presented in Chapter 3 was used for normalization. Figure 4.10 shows the result of normalization of response of Acetone for 4 sensors. The figure shows the normalized waveforms for all the heating waveform types.

![Figure 4.10](image-url)  
*Figure 4.10  Plot of normalized response waveforms of Acetone (4ul) for 4 sensors and various heating waveforms*
4.4 Feature Extraction

The feature extraction was accomplished by sampling one point every 5 seconds from each of the 50 point normalized response waveforms as was discussed in Chapter 3. The feature extraction was done for each of the heating waveform type. Each sensor resulted in 10 numbers of features for each waveform type. Since we have 4 optimized sensors set, therefore the length of the feature vector is 40. Each heating waveform type resulted in a feature vector of length 40. Figure 4.11 shows the result of normalization and extracted features from response of Acetone for 4 sensors. The figure shows the normalized waveforms and extracted features for all the heating waveform types.

Figure 4.11  Plot of normalized response waveforms and extracted features of Acetone (4ul) for 4 sensors and various heating waveforms
4.5 Best waveform determination

The classification accuracy of PARC engine depends on the quality of features. Different heating waveform varies the sensor temperature and reaction kinetics differently and produces different sets of features. The best heating waveform should produce the best set of features. To estimate the quality of the features produced from different heating waveforms, the Euclidean inter-intra cluster distance ratio discussed earlier in Chapter 3 may be used. The feature set (produced from the corresponding heating waveform) resulting in maximum value of the inter-intra cluster distance ratio better represents the cluster separation and therefore the corresponding heating waveform may be considered the best heating waveform.

In this research, we have therefore used the Euclidean inter-intra cluster distance ratio for feature (and the corresponding heating waveform) evaluation. We have used the same minimum value of the Euclidean inter-intra cluster distance ratio as discussed in Chapter 3 to represent the overall inter-intra cluster distance.

<table>
<thead>
<tr>
<th>Heating waveform</th>
<th>Euclidean inter-intra cluster distance ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rectangular</td>
<td>1.3058</td>
</tr>
<tr>
<td>Sinusoidal</td>
<td>1.2532</td>
</tr>
<tr>
<td>Sigmoid</td>
<td>1.3325</td>
</tr>
<tr>
<td>Sawtooth</td>
<td>1.0624</td>
</tr>
<tr>
<td>Triangular</td>
<td>0.859</td>
</tr>
<tr>
<td>Exponential</td>
<td>1.1173</td>
</tr>
<tr>
<td>Decreasing Sigmoid</td>
<td><strong>1.5594</strong></td>
</tr>
<tr>
<td>Decreasing Sawtooth</td>
<td>0.7224</td>
</tr>
<tr>
<td>Decreasing Exponential</td>
<td>0.6348</td>
</tr>
</tbody>
</table>
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ratio of the data set. Using the metric, the inter-intra cluster distance ratio of the entire data set consisting of 40 features as reported in section 4.5 was calculated for features of each of the heating waveform type. Table 4.1 lists the calculated Euclidean inter-intra cluster distance ratio for various waveforms. It is seen from the table that the inter-intra cluster distance ratio is maximum with a value of 1.5594 for the decreasing sigmoid heating waveform. Therefore the decreasing sigmoid heating waveform may be considered as the best waveform from among the 9 different waveforms for temperature modulation. The decreasing sigmoid heating waveform produces the best features with best cluster separation for better classification.

4.6 Conclusion

In this chapter, literature reviews of various temperature modulation waveform employed by different researchers were presented. Temperature modulation of MOS gas sensors results in characteristic response waveforms. In this work, 9 different temperature modulation waveforms were considered to evaluate the best waveform for better classification. Each cycle of the 9 different waveforms was of 50 seconds duration. An array of 4 optimized sensors TGS826, TGS821, TGS2611 and TGS825 obtained earlier were used for evaluation. The odour response data of 16 laboratory chemicals were obtained at two different concentrations for each of the heating waveforms. The response waveforms were filtered and sub-sampled and then normalized to yield a 50 point signal for each sensor. Features from the normalized signals were obtained by further sub-sampling the 50 point normalized signals by taking 1 response data every 5 seconds yielding 10 features form each sensor and a total of 40 features from 4 sensors. The features were extracted for each of the heating waveform.

In this work, the evaluation of all the heating waveforms was done to identify the best waveform for temperature modulation. The best waveform was determined in terms of the quality of features, the waveform produces. The
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The quality of the features was measured by the Euclidean inter-intra cluster distance ratio. The ratio was calculated for each of the heating waveform. The best value of inter-intra cluster distance ratio of 1.5594 was obtained using the decreasing sigmoid heating waveform. Hence the decreasing sigmoid heating waveform may be considered as the best waveform for temperature modulation to detect the 16 laboratory chemicals using the 4 optimized sensor set.

References


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