Abstract—Temperature modulation has been proved to be an efficient technique for improving the selectivity and stability of gas sensors. By retrieving information from dynamic signals, new response features are obtained that confer more selectivity to metal oxide sensors. Time-frequency and transient analysis have been widely used in this kind of dynamic signal processing. These methods represent important characteristics of a signal in both time and frequency domain. In this way, essential features of the signal can be viewed and analyzed in order to identify or quantify the detected gases. Very often the fast Fourier transform and the discrete wavelet transform have been used as feature extraction tools. This work presents the application of a new signal processing technique, empirical mode decomposition and the Hilbert spectrum, in analysis of dynamic response signals of gas sensors. Using EMD method, the dynamic signals were decomposed into the intrinsic modes that coexist in the sensor system, and to have a better understanding of the nature of the gas sensing response information contained in the sensor response signals. The experimental results show that marginal spectrum can be used as useful feature for identification. By this method, the intrinsic response components to the analyte may be provided and the extracted features are simple and having intrinsic physical meaning.

Keywords-gas sensor; temperature modulation; Hilbert-Huang transform; feature extraction

I. INTRODUCTION

Semiconductor gas sensors suffer from serious shortcomings such as poor selectivity, low repeatability and response drift. In order to overcome these disadvantages, several methods are carried out and they can be classified into three main groups: 1) strategies in material science (catalysts, filters, etc.), 2) strategies in sensor measurement (sensor array, static and dynamic measurements, etc) and 3) signal processing algorithms (pattern recognition methods, artificial neural networks, etc) [1-2]. Among the different approaches envisaged to fight the drawbacks, modulating the operating temperature of gas sensors has been remarkably successful in many applications. Temperature modulation alters the kinetics of the adsorption and reaction processes that take place at the sensor surface while detecting reducing or oxidizing species in the presence of atmospheric oxygen. This leads to the development of response patterns, which are characteristic of the species being detected. In other words, by retrieving information from response dynamics, new response features are obtained that confer more selectivity to metal oxide sensors. In deed, several authors have developed this strategy and applied several techniques to extract features that important for the discrimination or quantification of gases. Very often the fast Fourier transform and the discrete wavelet transform have been used as feature extraction tools [3-5].

In this paper, we introduce for the first time the Hilbert-Huang Transform (HHT) as alternative feature extraction methods to the more traditional FFT and DWT when the working temperature of micro-hotplate gas sensor is modulated. Recently, Hilbert-Huang Transform (HHT) which was proposed by N.E. Huang, et al in 1998 is a promising signal processing technique coping with nonlinear and non-stationary time series [6]. It has been used to process signals for many kinds of fields, such as the biological, physiological signals [7], voiced speech signals [8], the fault diagnosis [9-10], and so on. Comparing to other time-frequency techniques, HHT is based solely on the instantaneous frequencies resulting from the intrinsic mode functions of the signal being analyzed itself. It has attracted increasing attention in recent years.

The organization of the paper is as follows: Section II briefly introduces the theory of Hilbert-Huang Transform, and how it can be used to extract important characteristics from the dynamic response of gas sensors. Section III described the experimental setup for obtaining the carbon monoxide, methane and ethanol databases. In Section IV the results are presented and discussed. The conclusions derived from this work are presented in Section V.

II. FEATURE EXTRACTION METHOD BASED ON HHT

The nature of the sensing mechanisms ruling of chemical sensors is still far from full comprehension. The extraction of features from the response of chemical sensors consists in the selection of some characteristics of their temporal response sequence, which results from the interaction between sensors and the compounds to be detected. The extracted features are then input to pattern recognition systems. From a general point of view, a chemical sensor can be considered as a dynamic system whose response signal temporally evolves following, with its proper dynamics, the analytes and their concentration. Therefore, any of the currently available tools usually employed to study the properties of dynamic signals may be employed.
The Hilbert-Huang transform uses two steps to analyze the data. The first step is to decompose the data according to their intrinsic characteristic scales into a number of intrinsic mode function (IMF) components by using the empirical mode decomposition (EMD) method. In this way, the data are expanded in a basis derived from the data itself. The second step is to apply the Hilbert transform to the IMF components and construct the time-frequency-energy distribution, designated as the Hilbert spectrum. In this form, the time localities of events will be preserved, for frequency and energy defined by the Hilbert transform have intrinsic physical meaning at any point.

The EMD technique can decompose the original signal into a finite and a small number of intrinsic mode functions (IMFs). The obtained IMF must satisfy two conditions: 1) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one; 2) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero. In [6], the process of EMD was described in detail. Thus, the original signal $x(t)$ is the sum of the IMF components plus the residue:

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t)$$  \hspace{1cm} (1)

where $c_i(t)$ ($i=1,2,...,n$) are the IMF components, $r_n(t)$ is the residue, which can be either the mean trend or a constant.

The Hilbert transform is applied to each IMF, $c_i(t)$, to obtain $y_i(t)$, as

$$y_i(t) = \frac{1}{\pi} P\int_{-\infty}^{\infty} \frac{c_i(\tau)}{t-\tau} d\tau$$  \hspace{1cm} (2)

where $P$ indicates the Cauchy principal value. With this definition, $c_i(t)$ and $y_i(t)$ form a complex conjugate pair, so we can have an analytic signal, $z_i(t)$, as

$$z_i(t) = c_i(t) + jy_i(t) = a_i(t) e^{j\theta(t)}$$  \hspace{1cm} (3)

in which

$$a_i(t) = [c_i^2(t) + y_i^2(t)]^{1/2}$$  \hspace{1cm} (4)

$$\theta(t) = \arctan \frac{y_i(t)}{c_i(t)}$$  \hspace{1cm} (5)

The instantaneous frequency of the dynamic signal can be obtained as

$$\omega(t) = \frac{d\theta(t)}{dt}$$  \hspace{1cm} (6)

Having obtained the intrinsic mode function (IMF) components, the Hilbert transform is applied to each of these IMF components and computes the instantaneous frequency according to Equation (6). After performing the Hilbert transform to each IMF component, the original data can be expressed as the real part (Re) in the following form:

$$x(t) = \text{Re} \sum_{i=1}^{n} a_i(t) e^{j\omega_i(t) dt}$$  \hspace{1cm} (7)

Here we have left out the residue $r_n(t)$ on purpose, for it is either a monotonic function or a constant. Although the Hilbert transform can treat the monotonic trend as part of a longer oscillation, the energy involved in the residual trend could be overpowering. In consideration of the uncertainty of the longer trend, and in the interest of information contained in the other low-energy but clearly oscillatory components, the final non-IMF component should be left out. It could be included, however, if physical considerations justify its inclusion.

Equation (7) can represent the amplitude (or the energy), and instantaneous frequency as functions of time in a three dimensional plot. The HHT time-frequency spectrum can be obtained as following:

$$H(\omega,t) = \text{Re} \sum_{i=1}^{n} a_i(t) e^{j\omega_i(t) dt}$$  \hspace{1cm} (8)

Then the marginal spectrum can be defined as

$$h(\omega) = \int H(\omega,t) dt$$  \hspace{1cm} (9)

where $T$ is the total length of the signal. The marginal spectrum offers a measure of total amplitude (or energy) contribution from each frequency value. It represents the cumulated amplitude over the entire data span in a probabilistic sense. The contribution of the amplitude from each frequency is measured by the marginal spectrum.

The temperature modulation has a two-fold effect on the sensor signal. One is due to the straight relationship between resistance and temperature (thermistor effect) and the other is given by temperature dependence of the sensitivity to the gas. Indeed, it is rather well known that for each gas an optimal temperature ranges exists. The combination of these two effects gives rise to a complex signal not simply disentangled in the time domain. For most sensors, the resistance could be affected more by the thermistor effect. The information of detected gas is most covered in the temperature dependence of the sensitivity to the gas, which is shown weak in the dynamic signals. Therefore, it is necessary to extract this part out. Based on the HHT theory, it is quite hopeful to obtain the IMFs and the Hilbert spectra corresponding to the detected gases.

III. EXPERIMENTAL SETUP

The sensor used in this paper is the micro-hotplate (MHP) based thin film tin dioxide gas sensors. It is fabricated with silicon based surface micromachining technology [11]. The sensing film is SnO2 with the thickness of about 300nm. Pd is deposited onto the tin dioxide as the catalyst respectively, with the thickness of about 1nm.

All of the experiments are performed through an automated measurement system. Its schematic is shown in Figure 1. The AIR denotes the compressed normal clean environmental air. The GAS1, GAS2 and GAS3 are the5000ppm methane, 200ppm carbon monoxide and 50ppm Ethanol. The concentration of the gas flown into the chamber is determined by the ratio of the flow in the 4 pipes controlled by the 4 MFCs respectively. The detected sensors are mounted in the chamber.
Programmable voltage signals could be applied to heating the micro-hotplate gas sensor and its working temperature is modulated in a wide frequency range. The often used sinusoidal waves, rectangular waves and triangle waves could be applied to the sensor. In order to discriminate the three flammable gases with similar chemical characteristics, the dynamic response signals of the modulated sensor to methane, carbon monoxide and ethanol with different concentrations were tested and recorded.

IV. RESULTS AND DISCUSSION

In this part, the sensor operating temperature was modulated using a sinusoidal signal with different periods. The sampling frequency is 1Hz. Response of the sensor to 3000ppm methane, 150ppm carbon monoxide and 15ppm ethanol were obtained, shown in Figure 2. It can be seen that the curves to one gas at different modulating periods are similar except the small period. The influence of the constant sampling frequency could be a reason for the difference.

To testify the validity of the proposed method, the dynamic signals modulated with period of 20s are extracted out and decomposed with EMD. Figure 3 shows the original dynamic response signal and its IMFs. It can be seen that among the IMFs, there is one corresponding to the modulating signal which shows the similar frequency to the modulating voltage.

This verifies the theory. It also leads us to the conclusion that to extract a particular frequency component from a signal, it is not sufficient to select the IMF that produces that particular instantaneous frequency. In fact, a few neighboring IMFs that have instantaneous frequency that is equal to the desired frequency at certain instants need to be included too. Furthermore, to take into account the effect of noise and other irregularities in the signal, instead of a single frequency, a small band of frequencies centered on the

![Figure 1. Schematic of the experimental setup](image)

![Figure 2. The dynamic response signals with different modulating periods T=4s,10s,20s,30s,40s,50s,60s, the detected gas is 3000ppm CH₄, 150ppm CO and 15ppm Ethanol](image)

![Figure 3. The dynamic response and its IMFs (a) response to CH₄, (b) response to CO, (c) response to ethanol](image)
desired frequency is considered. The last IMF in each figure is the residue, which is the trend of steady resistance change.

The Hilbert transform is performed to the IMFs and the Hilbert-Huang spectrum $H(\omega, t)$ is obtained. Figure 4 gives the time-frequency graph for the three cases.

![Figure 4](image)

**Figure 4.** The Hilbert-Huang spectrum (a) response to CH$_4$, (b) response to CO, (c) response to ethanol

It can be seen from Figure 4 that there is a quite stable frequency signal around 0.05Hz during the whole time for all (a), (b) and (c). Because all the data are obtained from one sensor modulated with 0.05Hz sinusoidal signal, the thermistor effect is combined in the sensor response clearly. Respectively stable frequency components lower than 0.05Hz must be related with the detected gases. The marginal spectrum $h(\omega)$ of the IMFs are calculated and shown in Figure 5.

![Figure 5](image)

**Figure 5.** Marginal spectrum of IMFs. (a) response to CH$_4$, (b) response to CO, (c) response to ethanol

Analyzing the $h(\omega)$ of three cases, it can be seen that the frequency of 0.05Hz is quite clear in all the figures. This frequency is generated by the thermistor effect depending on the modulating signal. This is verified by the signals at the other periods. Although the 0.05Hz power spectrum is most related with the heating voltage, it is also an important feature for identifying gases, as the power at this frequency
are different, especially the CO gas. The peak value is up to 0.13 for CO, while for methane and ethanol, the peak value is around 0.05. If the frequency is only depending on the heating process, the power spectrum at this frequency must be the same for one single sensor. However, it is different now. Hence there must be the CO gas information among the frequency.

Except the 0.05Hz frequency, there are two relatively low peaks around the frequency of 0.02Hz and 0.04Hz all in (a) (b) and (c), but the peak values are different. For methane in (a), the peak value of 0.02Hz is larger. For CO in (b), the two peaks are similar and the lower frequency is larger too. For ethanol in (c), both the peak values are lowest. The peak values around the 0.02Hz, 0.04Hz and 0.05Hz are most essential features to identify the three gases. The spectra at higher frequencies are also different. For methane in (a), the distribution of the spectra is falling slowly from the peak at 0.02Hz. For CO in (b), the falling rate is larger. For ethanol in (c), it is almost a sudden change to 0 and then increases around 0.15Hz to 0.2Hz. The power spectra at high frequency could be the assistant features to identify the gases. The features of high frequency band could be extracted out as the input of pattern recognition algorithms.

V. CONCLUSION

In this paper, a feature extraction method for temperature modulated gas sensors was presented based on a newly developed signal processing technique named as Hilbert-Huang transform. The dynamic response signals to methane, carbon monoxide and ethanol of the sensors modulated with sinusoidal signals were measured with an automated measurement system. Using EMD method, the dynamic signals were decomposed into the intrinsic modes that coexist in the sensor system, and to have a better understanding of the nature of the gas sensing response information contained in the sensor response signals. The experimental result has been shown that marginal spectrum can be used as useful feature for identifying the three gases. Further results on quantification of gas concentrations are coming.

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