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The EMD Based IMF Analysis of Gas Sensor Dynamic Signals

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Abstract:
Temperature modulation has been proved an efficient technique for improving the selectivity of gas sensors. However, it suffers from the complex and subjective feature extraction processes. This paper introduces the empirical mode decomposition (EMD) method to obtain the intrinsic mode functions (IMFs) of the dynamic signals from the modulated gas sensor system. Instantaneous spectrum and its spectrum peaks are extracted from the IMFs as meaningful features, which not only improve the classification and quantification performance, but also give a better understanding of the nature of the temperature modulated gas sensor signals. Experimental results demonstrate its validity.

Key words: gas sensor, temperature modulation, empirical mode decomposition, intrinsic mode function

Introduction

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. By retrieving information from response dynamics, new response features are obtained that confer more selectivity to metal oxide sensors [1-4]. 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 Fast Fourier Transform and Discrete Wavelet Transform have been used as feature extraction tools [3-4]. However, most features extracted are more related with the pattern recognition approaches than sensors, and their meanings are not easy to analyze. Therefore, this paper introduces the empirical mode decomposition (EMD) method to extract the intrinsic mode functions (IMFs) of the dynamic signals. The IMFs are analyzed and more meaningful features are extracted and studied.

EMD Based IMF Extraction Method

EMD technique is the first step of Hilbert-Huang Transform (HHT) proposed by N.E. Huang, et al in 1998 [5], which has been a promising signal processing technique coping with nonlinear and non-stationary time series. It can decompose the original signal into a finite and a small number of IMFs. The decomposition is developed from the simple assumption that any data consist of different dimple intrinsic modes of oscillations. Each mode may or may not be linear, and will have the same number of extrema and zero-crossings. Further more, the oscillation will also be symmetric. Thus, an IMF is defined to satisfy two conditions: a) in the whole data set, the number of extrema and the number of zero crossings must either equal or differ at most by one; b) at any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

Thus, the original signal $\boldsymbol{x(t)}$ is denoted as the sum of the IMF components plus the residue:

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

where $\boldsymbol{c_i(t)}$ (i=1,2,…,n) are the IMF components, $\boldsymbol{r_n(t)}$ is the residue, which can be either the mean trend or a constant. The IMFs are obtained from a sifting process, which is given as [6]:

(a) Identify all the local extrema,

(b) Connect all the local maxima (minima) by a cubic spline line as the upper envelope(the lower envelope),

(c) Calculate the mean of the envelopes,

(d) Extract the IMF from the signal.

(e) Iterate on the residual.

Having obtained the IMF components, the Hilbert transform is applied to each of these IMF components and computes the instantaneous frequency. The equations are shown as (2)-(4).

$$H(\omega,t) = \mathrm{Re}\sum_{i=1}^{n} a_i(t)e^{j\int \omega_i(t)dt} \quad (2)$$

$$a_i(t) = \sqrt{[c_i^{\,2}(t) + y_i^{\,2}(t)]} \quad (3)$$

$$\omega_i(t) = \frac{d\theta_i(t)}{dt} = \frac{d}{dt}[\arctan\frac{y_i(t)}{c_i(t)}] \quad (4)$$

Where $c_j(t)$ is the jth IMF component, $y_i(t) = \frac{1}{\pi}P\int \frac{c_i(\tau)}{t-\tau}d\tau$ is the Hilbert transform of $c_j(t)$, P indicates the Cauchy principal value. $\omega_j(t)$ is the instantaneous frequency of the $c_j(t)$, $a_j(t)$ represents its amplitude. Then the marginal spectrum can be defined as

$$h(\omega) = \int_0^T H(\omega,t)dt \quad (5)$$

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.

IMFs of Gas Sensor Dynamic Signals

It is found that temperature modulation has a two-fold effect on the sensor signal, including the thermistor effect and gas sensing effect. Thermistor effect comes from the temperature dependence of the sensor itself, and the gas sensing effect comes from the temperature dependence of the sensor's sensitivity to gases. Combination of these two effects gives rise to a complex signal not simply disentangled in time domain. In most cases, gas information is largely covered by the temperature dependence of gas sensors, which is very weak in the dynamic signals. Therefore, to extract out the gas information is the purpose of gas sensor dynamic signal processing methods.

A batch of microhotplate gas sensors are modulated with a set of temperature waves, including sine, rectangular, triangular and sawtooth waves with different periods and amplitudes. The 100°C-300°C temperature range is chosen, and the periods are designed as 10s, 20s, 30s, 40s, 50s, and 60s. Modulated by the above modes, sensor responses to methane (CH_4), monoxide (CO) and ethanol are measured through an automated test system. The concentrations of CH_4, CO and ethanol are set 3000ppm, 150ppm and 15ppm. The test procedure is 15min clean air, 5min CH_4, then 15min clean air, 5min CO, and finally 15min clean air, 5min ethanol.

The obtained dynamic signals are processed with the proposed EMD method. Fig.1 shows an original dynamic signal response to 3000ppm methane and its IMFs (c1, c2 and c3, c4 is the residue) decomposed by EMD. The sensor is modulated by a rectangular waveform with period of 20s, amplitude of 100-350°C. It can be seen that the voltage across the sensor is low at higher temperature, while high at low temperature, which is mostly controlled by the temperature and still a rectangular wave. After EMD, there is one IMF corresponding to the modulating signal which shows the similar frequency to the modulating voltage.

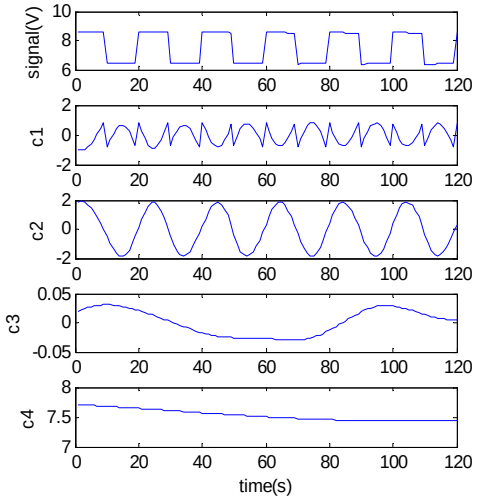

Fig.1 Dynamic signal and its IMFs

Its time-frequency spectrum $H(\omega,t)$ is computed and shown in Fig.2. It can be seen that there are mainly four frequency components with variable distribution in time domain.

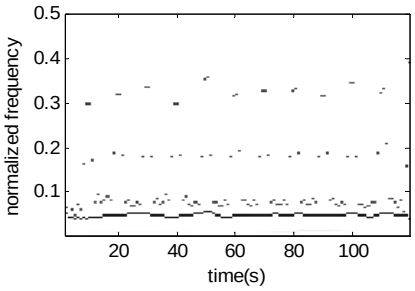

Fig.2 Time frequency spectrum of signal in methane

In order to further analyze the dependence of the frequency signal upon time domain, the instantaneous frequency spectrum of each IMF is calculated and shown in Fig.3. The frequency component of c1 IMF is some periodical. The c2 IMF frequency is likely 0.05Hz, which is the base frequency of the temperature modulation mode.

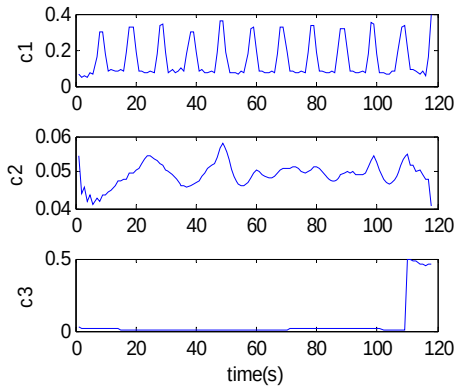

Fig.3 the instantaneous frequency spectrum of IMFs (c1, c2, c3) in Fig.1

The power spectrum corresponding to Fig.3 is shown in Fig.4. It can be seen that c1 IMF contains 4 major frequency bands, c2 IMF shows strong single frequency at 0.05Hz. c3 IMF also is a single frequency but its amplitude is small.

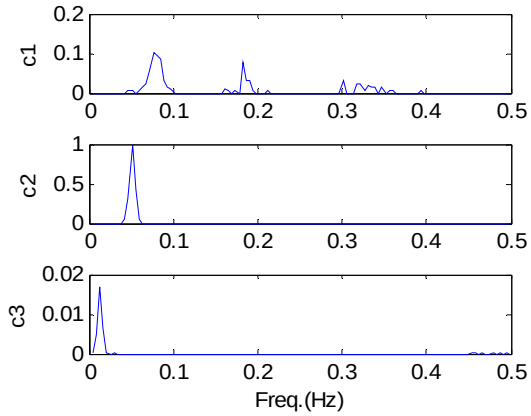

Fig.4 the marginal spectrum of IMFs (c1, c2, c3) in Fig.1

The contribution of each frequency components to total signal in methane is clearly shown as the red dotted line in Fig.5. It can be seen that the 0.05Hz modulation frequency occupies most energy, while the other frequency components occupy relative small energy.

For comparison, the sensor responses in clean air, 150ppm CO and 15ppm ethanol under same modulation mode are processed with the above procedure. And the marginal spectrum of are shown in Fig.5. It can be seen that spectrum pattern of ethanol is absolutely different with other gases. For methane, CO and air, amplitude of similar 0.05Hz frequency is quite clear and occupies most energy in total signal spectrum, while the peak values are different.

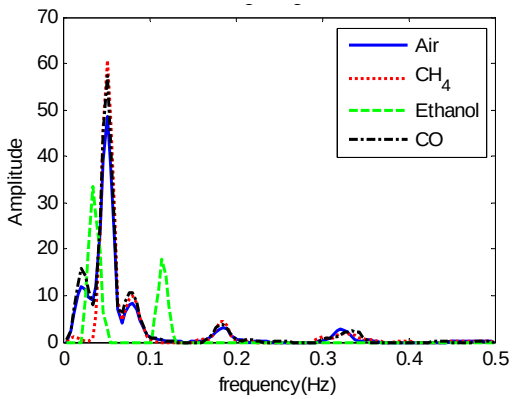

Fig.5 the marginal spectrum of the signals response to 3000ppm CH_4,150ppm CO and 15ppm Ethanol

The Instantaneous Frequency Features

Features most related with the detected gases should be extracted out as the inputs of the following pattern recognition system. These features are not only on behalf of the gas classifications, but also have smallest sensitivity to gas concentrations, environmental temperature and humidity, stability of sensors, etc. From the above analyses, the amplitude and location of the instantaneous frequencies are different among the different detecting situations.

The peak values of marginal spectrum and their locations are extracted as features to identify detected gases, shown in Fig.6. It can be seen that the features are different and can be used to recognize the detected methane (CH_4), carbon monoxide (CO) and ethanol. The frequency of 0.05Hz is quite clear and occupies the most energy in response to air, CO and CH_4, while different to ethanol. 0.05Hz is generated by the thermistor effect.

The influences of modulation periods are studied. The dynamic signals in the detected gases modulated with rectangular waves of

periods 4s, 10s, 20s, 30s, 40s and 60s. The peak values and locations are extracted out and shown in Fig.7 and Fig.8 relatively. Fig.7 shows the relationship of the location of peaks, which are the central frequency of peaks, with the periods. The abscissa values of 1 to 6 denote the period 4s, 10s, 20s, 30s, 40s and 60s. It can be seen that the central frequency of the marginal spectrum peak decreases when the period increases. And the central frequency is the same as the temperature wave frequency. This is mainly caused by the modulated temperature.

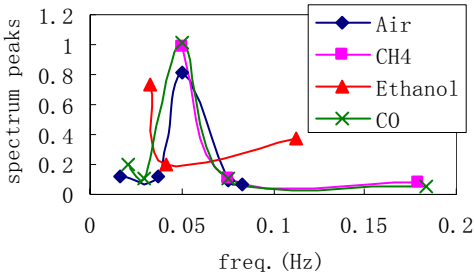

Fig.6 The spectrum peaks of the signals response to 3000ppm CH4, 150ppm CO and 15ppm Ethanol

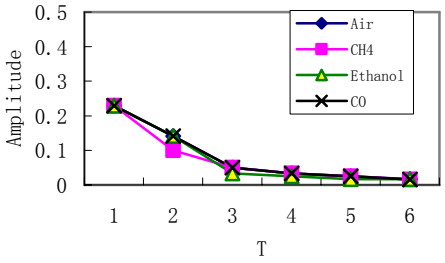

Fig.7 Relationship between the peak locations and modulation periods

The dependence of peak values on modulation periods are shown in Fig.8. It shows that, as increasing the period, the peak values show a trend of decreasing, which means the power spectrum are distributed into other frequency components. That is, the influence of temperature on dynamic signals is decreasing. This demonstrates that sensor response to detected gas is some kind of slow changing signal. The response time of gas sensor is large. Therefore, to strengthen the gas information, larger period is better for rectangular waves. However, when period is 40s and 60s, the peak values increase a little. This illustrates that the period should be set not too long. In our experiments, middle period is valuable for gas information.

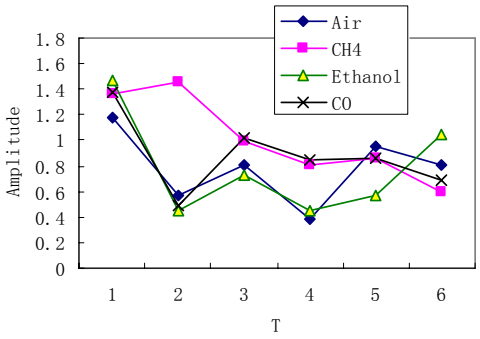

Fig.8 Relationship between the peak values and modulation periods

Conclusion

EMD technique is studied and introduced to process the temperature modulated gas sensor dynamic signals. Based on the EMD and Hilbert transform, the time-frequency spectrum can be used to describe the original signal. The IMFs decomposed by EMD illustrate the dynamic signal contains some strong thermister information and some weak gas information. Peak values and locations of marginal spectrum are extracted out to describe the gas patterns. According to their relationship with modulation periods, optimal period could be chosen out.

Acknowledgements

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