Application of Hilbert-Huang Transform and SVM to Coal Gangue Interface Detection

Wei LIU*
School of Information and Electronics Engineering,
Shandong Institute of Business and Technology, Yantai, P R CHINA
lwairee@gmail.com

Yuhua YAN
Shandong Business Institute, Yantai, P R CHINA
yanyuhua@126.com

Rulin WANG
China University of Mining & Technology, Beijing, P R CHINA
rulinwang@yanhoo.com.cn

***Abstract*— In order to detect coal gangue interface on fully mechanized mining face, a new method of vibration signal analysis of coal and gangue based on Hilbert-Huang transform is presented in this paper. At first Empirical mode decomposition algorithm was used to decompose the original vibration signal of coal and gangue into intrinsic modes for further extract meaningful information contained in response signals under complicated environment. By analyzing local Hilbert marginal spectrum and local energy spectrum of the first four intrinsic mode function components, we found the difference of coal and gangue at specific frequency interval that the amplitude and energy mainly distributed at frequency interval between 100Hz and 600Hz when coal fell down, while the amplitude and energy were more concentrated at 1000Hz or so when gangue fell down. Furthermore, the further analysis result from marginal spectrum of each intrinsic mode function component agreed well with the conclusion above. Combined with time-domain parameters, we defined the energy function based on the above feature as inputs of support vector machine for simulation experiment. The results show that the extracted features with the proposed approach can be served as coal gangue interface recognition.**

***Index Terms* - fully mechanized mining face , vibration signal , coal gangue Interface detection, Hilbert-Huang transform, empirical mode decomposition, support vector machine**

I. INTRODUCTION

Coal gangue Interface detection (CGID) is not yet been solved on fully mechanized mining face. The working procedure of top-coal caving is programming controlled by electro hydraulic system, which determines coal caving time, recovery ratio of top-coal and the percentage of gangue content. To improve the coal recovery ratio, lots of works have been done on CGID. According to the different mechanical properties between coal and gangue, it has been applied to detect coal gangue interface based on the responses of coal shearer’s cutting force [1-2]. By measuring the decay intensity of natural Gamma ray to estimate thickness of top coal seam, it can be served as identification of coal gangue interface, but it is required that roof and floor of surrounding rock must contain natural radioactive elements[3-6]. Using infrared ray and acoustic signal to detect CGID is also explored [7-9]. However, these methods mentioned above have remained rarely practical application.

This paper presents a new CGID method by analyzing vibration signal of coal and gangue. Some significant features can be found by analyzing the vibration signal of coal and gangue with different granularity and proportion. However, the acquired vibration signal is nonlinear and non-stationary, so it is a very difficult problem to extract the features contained in time domain signal. 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 [10-13]. It has been used to process signal for many kinds of fields, such as the biological signals, speech signals, fault diagnosis [14-18] and so on. HHT is based on instantaneous frequencies resulting from intrinsic mode function of signals, which is different from traditional FFT and DWT. So we introduce for the first time the HHT as feature extraction of vibration signal of coal and gangue.

On the other hand, pattern classification method is another key point for CGID. Conventional statistical pattern recognition methods and artificial neural networks (ANN) classifiers are studied based on the premise that the sufficient samples are available, which is not always true in practice [19]. Support Vector Machines (SVM) is a very effective method for general purpose pattern recognition based on structural risk minimization principles [20]. It is of specialties for a smaller sample number have better generalization than ANN and guarantee the local and global optimal solution are exactly

Supported by National Natural Science Foundation of China (60970105)
* Corresponding author. Tel:+86-535-6887702.
Email:lwairee@gmail.com

doi:10.4304/jcp.6.6.1262-1269

the same. Meantime, SVM can solve the learning problem of a smaller number of samples. This characteristic is very important in fault diagnostics, speech recognition and text categorizations. In recent years, SVM have been found to be remarkably effective in many applications [21-25].

In this paper, Hilbert-Huang transform is applied to feature extraction for vibration signal of coal and gangue. These features are served as inputs of SVM classifier to detect CGID. The paper is organized as follows: In the next section, we introduce the principle of CGID experimental system. Section III and IV reviews the HHT technique and SVM theory briefly. Section V mainly discusses how the HHT can be used to extract important features from original vibration signal and the experimental results are presented. Then SVM is implemented to train and testify samples and the results are reported. Finally the conclusion is drawn in the last section.

II. PRINCIPLE OF EXPERIMENTAL SYSTEM

The fully mechanized mining face includes mining working surface and top coal caving working surface. The experimental system is composed of vibration acceleration sensor and portable acquisition terminal. As shown in Fig. 1, the acceleration sensor installed on the hydraulic support acquires vibration signal of coal and gangue impacting with steel plate of tail boom. The sampling time, amplitude and sampling frequency are stored in portable acquisition terminal. At least two sensors as a sensor array connect with CGID system for multi-channel acquisition. During the coal caving, if the content of gangue exceeds certain proportion, CGID system will send instruction to electro hydraulic system.

CGID system includes three main parts: vibration signal accquition, feature extraction, pattern classfication [26-27].

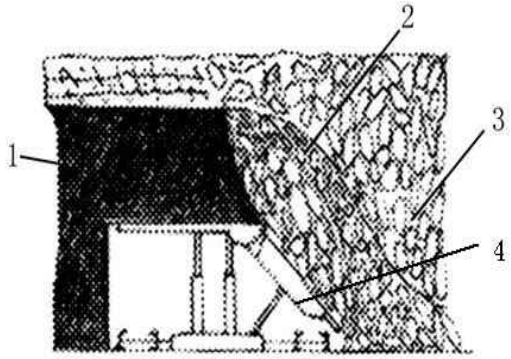

Figure 1. Hydraulic support and position of sensor (1.coal seam 2. coal mixed gangue 3.ganaue seam 4.sensor)

III. HILBERT HUANG TRANSFORM

A. Empirical mode decomposition

A novel non-linear and non-stationary signal analysis technology, named Hilbert-Huang transform is proposed by Norden E. Huang from NASA. This method can decompose any time varying signal into its fundamental intrinsic oscillatory modes with the so-called empirical mode decomposition (EMD). Applying the Hilbert transformation to any of these disintegrated intrinsic mode functions (IMF) subsequently provides the Hilbert spectrum with significant instantaneous frequencies.

Comparing to other time-frequency analysis methods, HHT utilizes intrinsic mode function with time locality to obtain instantaneous frequency with practical physical meaning. It is assumed that original signal contains a number of IMF component, which must satisfy two conditions:

1) In the whole data set, the number of extrema and the number of zero crossing 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.

The EMD technique can decompose the non-stationary original signal into a finite and the sum of the IMF components which satisfy the two conditions above.

Supposed that these is a time series $X(t)$, the process of EMD was described in the following steps:

Step 1: Initialize $R_0(t) = X(t)$, $i=1$ and $h_0(t) = R_{i-1}(t)$, $j=1$.

Step 2: Extract the local minima and maxima of time series $h_{j-1}(t)$. Interpolate the local maxima by a cubic spline to form upper envelope H_{up} of $h_{j-1}(t)$. And construct the lower envelope H_{low} of $h_{j-1}(t)$ by fitting all the local minima with cubic spline. The upper and lower envelopes should cover all the data between them.

Step 3: We calculate the mean value of the envelopes by $m_{j-1}(t) = (H_{up} + H_{low})/2$. The difference between $h_{j-1}(t)$ and its mean is $h_j(t) = h_{j-1} - m_{j-1}$.

Step 4: If $h_j(t)$ meets the criteria of an IMF, designate this $h_j(t)$ as IMF component $C_i(t)$. If $h_j(t)$ is not an IMF, then increment j, return to step 2 and repeat the procedure.

Step 5: Define the residue as $R_i(t) = R_{i-1}(t) - C_i(t)$. If $R_i(t)$ meets the stop criteria, the whole sifting procedure should stop. If not, increase i and return to step 1. We set the final stop criterion to be that $R_i(t)$ has a predetermined number of extreme. This criterion is less strict than the original one and will result in a quicker stop. Such adaptation won't affect the signal extraction in our situation since the residue with limited extreme will only contribute to lower frequency.

So the original time series signal $X(t)$ can be expressed as the sum of the IMF components and the residue:

$$X(t) = \sum_{i=1}^{n} C_i(t) + R_n(t) \tag{1}$$

where $C_i(t)$ are the IMF components, and $R_n(t)$ is the residue, which can be either mean trend or a constant.

The essence of EMD is to identify the intrinsic oscillatory modes by their characteristic time scales in the data accordingly. The IMFs are produced directly from the signal itself, so they are adaptive according to the signal intrinsic characteristics. And the decomposition components are more meaningful as they are identified by their physical nature.

The vibration acceleration signal of top coal and gangue is usually non-linear and non-stationary, so it is a

very difficult problem to extract usefully features contained in time series signals under complex environment. After EMD, original vibration signal has usually been decomposed into a small number of IMFs. Then we extract the IMFs which contains mostly the information of coal and gangue, and discard those are mainly clutter and noise. Thus the signal to disturbance ratio can be greatly improved. And the signal of interest can be clearly displayed in the time frequency domain.

B. Hilbert spectrum

HHT technique can be described as two steps. The first step is to decompose signal into IMFs. The next step is to apply Hilbert transform to the IMF components and construct the time-frequency-energy distribution, that is, Hilbert spectrum. The Hilbert transform is applied to each IMF component $C_i(t)$ to obtain $H[C_i(t)]$ as follows:

$$H[C_i(t)] = \frac{1}{\pi}\int_{-\infty}^{+\infty}\frac{C_i(\tau)}{t-\tau}d\tau \tag{2}$$

and we can construct an analytic signal, $Z_i(t)$, as

$$Z_i(t) = C_i(t) + j\,H[C_i(t)] = \alpha_i(t)exp(j\theta_i(t)) \tag{3}$$

So defines time-varying amplitude function, $\alpha_i(t)$ and phase function, $\theta_i(t)$, as

$$\alpha_i(t) = \sqrt{C_i^2(t) + H^2[C_i(t)]} \tag{4}$$

$$\theta_i(t) = \arctan\frac{H[C_i(t)]}{C_i(t)} \tag{5}$$

The instantaneous frequency of non-stationary signal can be calculated as

$$\omega_i(t) = \frac{d\theta_i(t)}{dt} \tag{6}$$

Thus, after applying the Hilbert transform to each IMF component, the original signal $X(t)$ can be denoted as real part in the following form:

$$\begin{aligned} X(t) &= Re\sum_{i=1}^{n}\alpha_i(t)exp[j\theta_i(t)] \\ &= Re\sum_{i-1}^{n}\alpha_i(t)exp[j\int\omega_i(t)dt] \end{aligned} \tag{7}$$

Equation (7) is denoted as $H(\omega, t)$, which represent the amplitude and instantaneous frequency as function of time in a three dimensional plot. Then the marginal spectrum and the marginal energy spectrum can be defined as

$$h(\omega) = \int_0^T H(\omega,t)dt \tag{8}$$

$$E(\omega) = \int_0^T H^2(\omega,t)dt \tag{9}$$

where T is the sampling length of signal. The marginal spectrum offers a measure of total amplitude or energy contribution from each frequency.

HHT satisfies the requirements of locality and adaptivity for non-stationary vibration signal analysis. Instantaneous amplitude and frequency can be obtained with the Hilbert transform. Thus the signal can be locally and accurately displayed in the time frequency domain by the Hilbert spectrum. On the other hand, EMD acts as an adaptive data-driven filter bank which makes it possible to dynamically extract the signal feature from disturbance according to their different physical characteristics. EMD is more efficient than the conventional frequency-domain filtering for noise rejection.

IV. REVIEW OF SUPPORT VECTOR MACHINE

The SVM was introduced by Vapnik in the late 1960's on the foundation of statistical learning theory. SVM is a new generation learning system enabling nonlinear mapping of an n-dimensional input space into a high-dimensional feature space. The SVM can train nonlinear models based on the structural risk minimization principle that seeks to minimize an upper bound of the generalization error rather than minimize the empirical error as implemented in other neural networks. This induction principle is based on the fact that the generalization error is bounded by the sum of the empirical error and a confidence interval term depending on the VC dimension. Based on this principle, SVM will achieve an optimal model structure by establishing a proper balance between the empirical error and the VC confidence interval leading eventually to a better generalization performance than other neural networks models.

An additional merit of SVM is that training SVM is a uniquely solvable quadratic optimization problem, and the complexity of the desired solution, rather than on the dimensionality of the input space. Hence, SVM utilize a non-linear mapping to transform an input space to high-dimension space based on a kernel function and then find a non-linear relation between inputs and outputs in the high dimension space.

It can be considered that SVM to creates a line or a hyper-plane between two sets of data for classification. Supposed that there is a given training sample set (x_i, y_i), each sample $x_i \in R_d$, $y_i \in \{+1, -1\}$, i=1, 2,…,n. The classification boundary can be described as follows:

$$w \cdot x + b = 0 \tag{10}$$

where w is a weight vector and b is a bias. So the following decision function can be used to classify any data set in two classes:

$$f(x) = sgn(w \cdot x + b) \tag{11}$$

The optimal hyper plane separating the data can be obtained as a solution to the following constrained optimization problem:

Minimize $$\frac{1}{2}\|w\|^2 \tag{12}$$

Subject to $$y_i[(w \cdot x_i)+b]-1 \geq 0,\ i=1,\ldots,n \tag{13}$$

Defined Lagrange multipliers $\alpha_i \geq 0$, the optimization problem can be converted to

Minimize

$$L(w,b,\alpha)=\sum_{i=1}^{n}\alpha_i-\frac{1}{2}\sum_{i,j=1}^{n}\alpha_i\alpha_j y_i y_j (x_i \cdot x_j) \tag{14}$$

Subject to $$\alpha_i \geq 0,\quad \sum_{i=1}^{n}\alpha_i y_i = 0 \tag{15}$$

Thus the decision function can be obtained as follows

$$f(x)=sgn(\sum_{i=1}^{n}\alpha_i y_i (x_i \cdot x)+b) \tag{16}$$

If the linear boundary in the input spaces is not enough to separate into two classes properly, it is possible to create a hyper plane that allows linear separation in the higher dimension. It can be achieved by using a transformation $\phi(x)$ that mapping the input data from input space to feature space. Defined a kernel function as follows,

$$K(x,y)=\phi(x)\cdot\phi(y) \tag{17}$$

which is introduced to perform the transformation, so the basic form of SVM can be rewritten

$$f(x)=sign(\sum_{i=1}^{n}y_i\alpha_i K(x_i,x)+b) \tag{18}$$

When the training data are not linearly separable in feature space, the optimization problem cannot be solved, since no feasible solution will exist. To allow for the possibility of samples violating constrains, slack variables are introduced. A classier which generalizes well is then found by controlling both the classier capacity and the number of training error.

This distinguishing function is the so-called as SVM. Linear kernel, polynomial kernel, RBF kernel and sigmoid kernel function are commonly used to map inputs.

V. EXPERIMENTS RESULTS AND DISCUSSION

To testify the validity of the proposed method, the HHT technique is applied to analysis of vibration signal of coal and gangue. The test data are derived from experimental system described in section II. Fig. 2 and Fig. 3 present two vibration signals of top coal and coal mixed with gangue, with sampling frequency at 8000 Hz and sampling time in 512ms. From Fig. 3, we find the shock characteristic at time 0.3s and 0.37s or so, which proves that gangue fall down with coal at that time possibly.

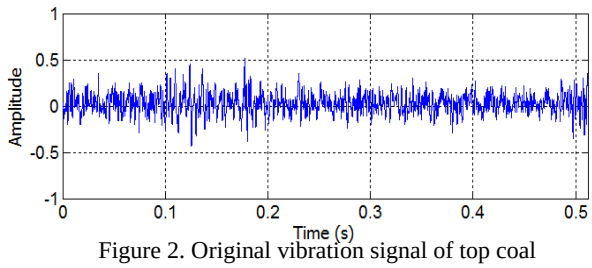

Figure 2. Original vibration signal of top coal

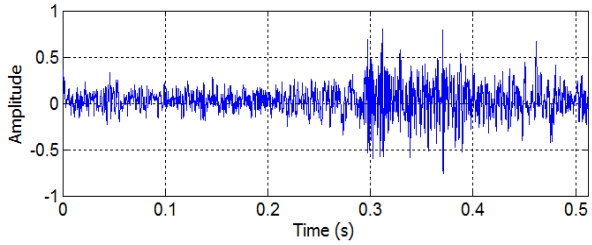

Figure 3. Original vibration signal of coal mixed with gangue

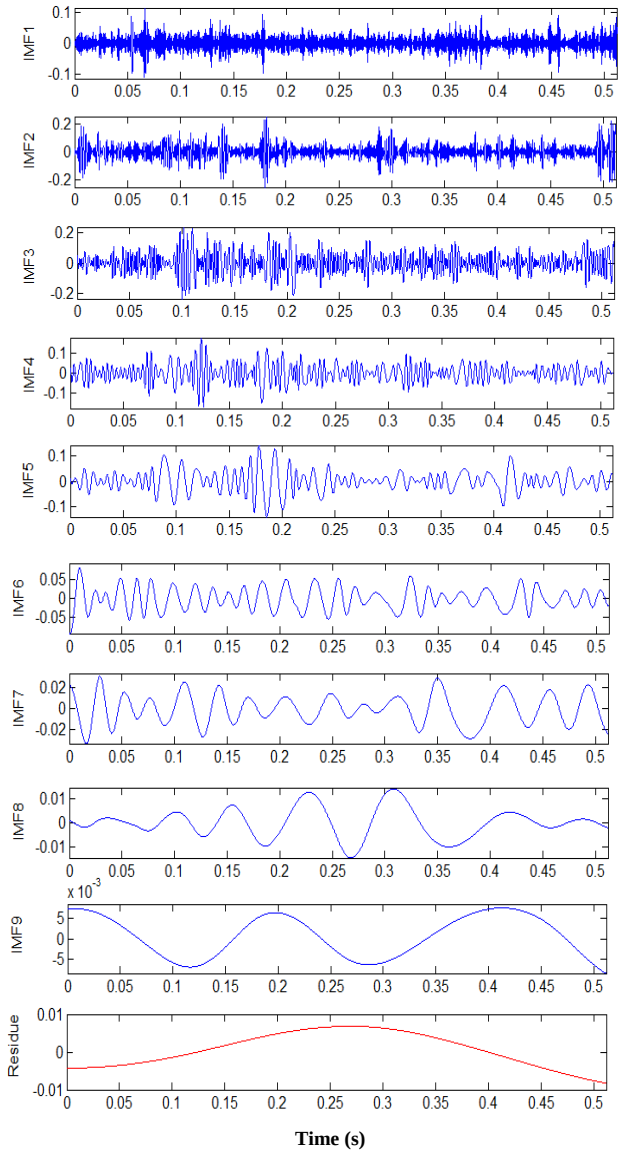

Figure 4. EMD result of top coal

A. EMD for original vibration signal

Then EMD is performed to decompose these two original signals into 9 IMFs. The last component is the residue. As shown in Fig. 4 and Fig. 5, the results proved EMD to be a sifting process which picks out the highest frequencies of the signal. Obviously, IMF1, IMF2, IMF3 and IMF4 have much higher frequencies than other components. Components from IMF5 to the residue oscillate so slowly that they may only contain very small frequencies.

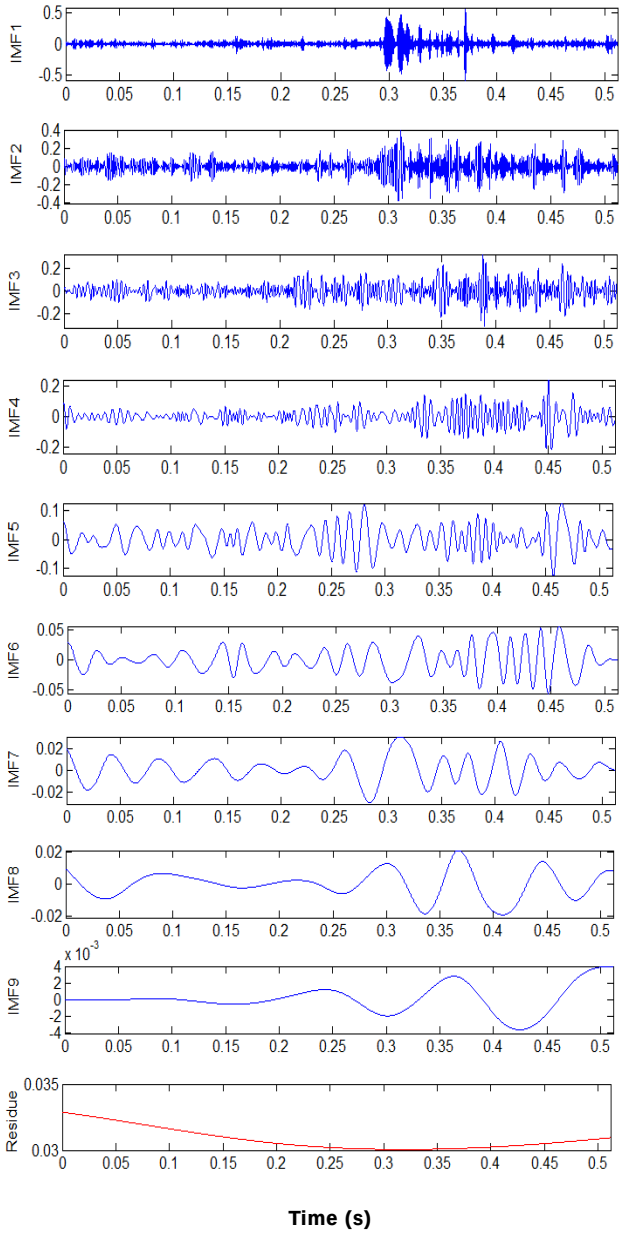

Figure 4. EMD result of top coal mixed with gangue

From the Fig. 5 we also find that the first four IMF components have either much higher frequencies or much larger amplitude around 0.3s and 0.37s, especially IMF1 and IMF2 components. Thus we select the first four components for further analysis.

B. Local marginal spectrum and local marginal energy spectrum

The Hilbert transform is performed to the IMFs and the Hilbert-Huang spectrum $H(\omega, t)$ is obtained. The marginal spectrum and marginal energy spectrum of the IMFs are calculated as equation (8) and (9). Now we attempt to apply Hilbert transform to the IMFs only from IMF1 to IMF4, we can get the local Hilbert marginal spectrum and local marginal energy spectrum.

It is shown that Fig. 6 is local marginal spectrum when only coal falls down, while Fig. 7 is local marginal spectrum when coal mixed with gangue fall down. Analyzing the Fig. 6 and Fig. 7, we can draw conclusion as follows:

1) When coal fall down without gangue, the amplitude or energy is larger between 100Hz and 600Hz, but smaller over 800Hz.

2) When coal mixed gangue fall down, the total amplitude or energy is larger. Especially around the frequency of 1000Hz, there are local peak values. Furthermore we found that the envelopes of curve are similar around (100, 600) Hz whether gangue exists or not.

C. Hilbert marginal spectrum of IMFs

To further prove the conclusion, we apply Hilbert magrinal spectrum to IMF1, IMF2, IMF3 and IMF4, respectively, giving the results in Fig. 8 and Fig. 9.

Both the Fig. 8 and Fig. 9 illustrate that the central frequency of IMF3, the same as IMF4, which considered as enviromental noise, such as vibration signal of conyeor. Although the amplitude of IMF2 in Fig. 8 is a little larger than that in Fig. 9, the central frequency is around 500Hz for all. So IMF2 component mainly contains the most information about coal. Comparing with IMF1 component, the central frequency of IMF1 in Fig. 9 is around 1000Hz. Meanwhile, its amplitude is much larger than that in Fig. 8. Thus it can be conclued that IMF1 component contain more information about gangue. So these features can be used in CGID.

D. SVM classification

As dicussed in previous sections, when coal mixed gangue fall down, the energy of IMF1 component around 1000Hz, that is , between 800Hz and 2500Hz, is much stronger , so we define feature energy function as follows

$$S = \int_{800}^{2500} h^{'}(\omega) d\omega \tag{19}$$

where $h^{'}(\omega)$ is local marginal spectrum of IMF1. Because the root mean square, variance and kurtosis can also reflect the mutation of signal, we choose the feature value S combined with the above three time domain features as inputs and establishes SVM classifier to detect coal gangue interface.

CGID is actually considered as a two-class classification problem. SVM has the advantage of a two-class classification based on the search for structural risk minimization, supported by few learning samples. When the feature input is a sample from the state of top coal

falling down, the output of SVM is set to +1, otherwise is set to -1.

The training experiments were conducted on a small data set consisit of 10 vibration signal samples, 5 signals for each of two states. At first, the root mean square *R*, variance *V*, and kurtosis *K* of time domain signals were caculated. The feature energy *S* could be caculated after EMD and hilbert transformation. The sample data were shown in Table 1, which were normalized to the interval between 0.1 and 0.9.

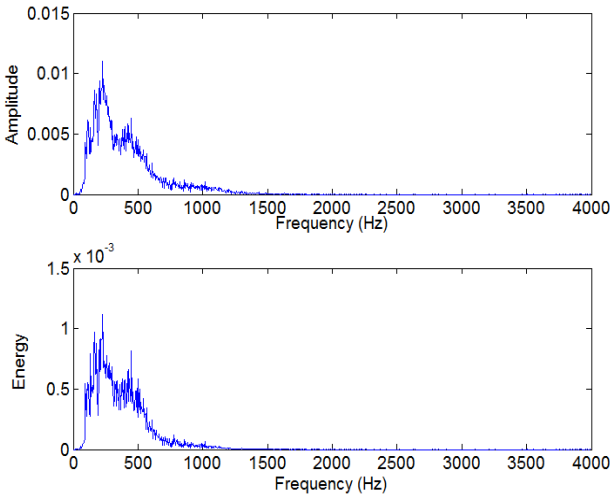

Figure 6. Local marginal spectrum and local marginal energy spectrum of top coal

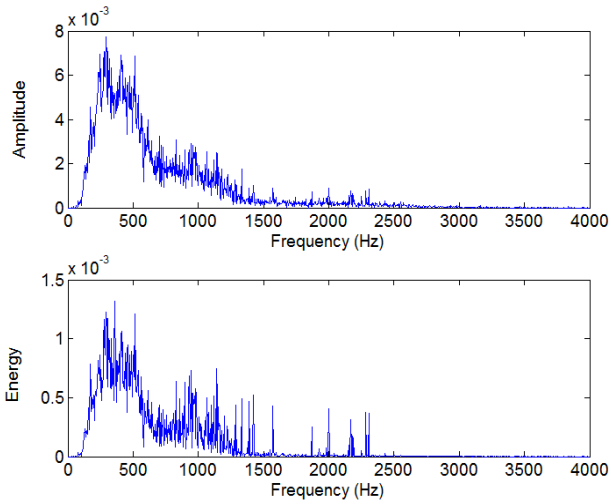

Figure 7. Local marginal spectrum and local marginal energy spectrum of coal mixed with gangue

The software platform of SVM classfication experiments was composed of windows 7 operating system, matlab 2007a and LIBSVM algorithm. Then, another 6 signals were used as a testing sample(4 signals for the state of top coal falling down and others for the state of coal mixed gangue falling down). The classification results are shown in Table 2. It is clear that SVM classifer detects coal gangue interface correctly.

In order to test the performance of SVM in the case of few samples, 6 signals were rechosen from Table 1 for trainning. The classification results of this test experiment are also accurate and prove the reliability of the SVM classifier.

VI. CONCLUSION

In this paper we applied HHT technique to extract the vibration signal feature of coal and gangue for CGID during top-coal caving on fully mechanized mining face. EMD is implemented to decompose original vibration signal into intrinsic mode functions and the associated

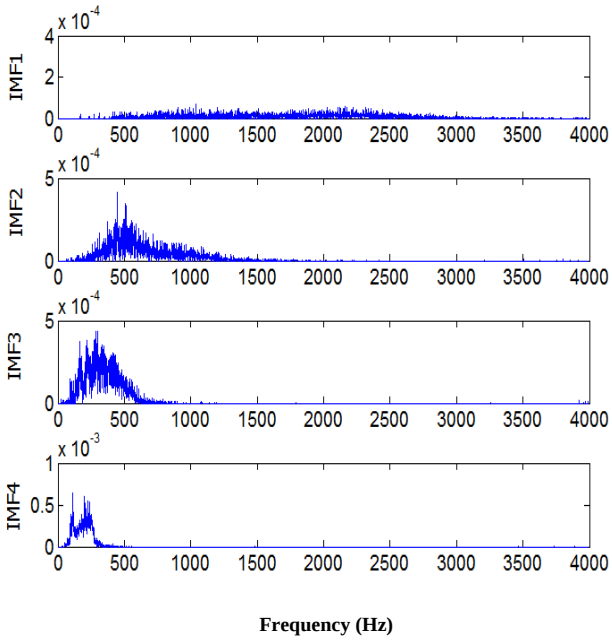

Figure 8. Marginal spectrum of IMF1, IMF2, IMF3, IMF4 for top coal

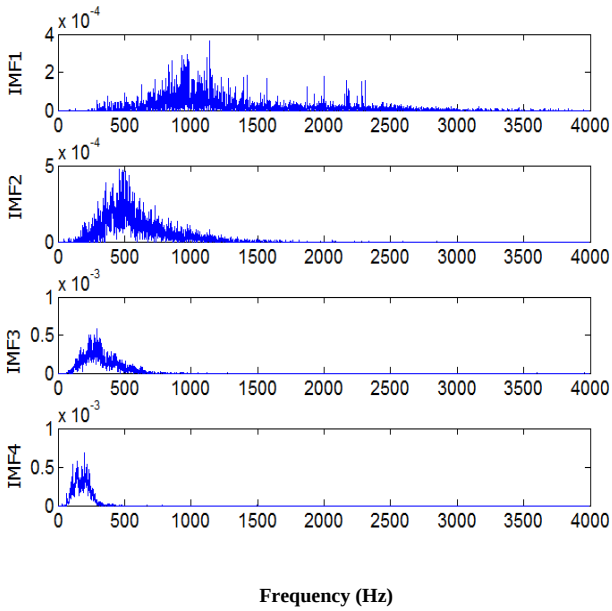

Figure 9. Marginal spectrum of IMF1, IMF2, IMF3, IMF4 for top coal

Table 1 Sample data

	S	*R*	*V*	*K*	*y*
1	0.1402	0.1198	0.1000	0.1000	+1
2	0.9000	0.6198	0.9000	0.6875	-1
3	0.1273	0.1000	0.1180	0.1675	+1
4	0.6558	0.7166	0.4870	0.5500	-1
5	0.7088	0.8326	0.5922	0.5850	-1
6	0.6783	0.9000	0.6570	0.9000	-1
7	0.1000	0.2915	0.1855	0.1500	+1
8	0.5514	0.3554	0.2233	0.1925	+1
9	0.2558	0.3685	0.2314	0.2725	+1
10	0.7040	0.6877	0.4636	0.6625	-1

Table 2 Classification results of SVM

	S	*R*	*V*	*K*	SVM outputs	results
1	0.5563	0.8572	0.6515	0.7312	-1.8308(-1)	right
2	0.6614	0.5970	0.7813	0.5314	-1.1576(-1)	right
3	0.4858	0.3438	0.7118	0.3922	-0.1634(-1)	right
4	0.4066	0.5833	0.8713	0.3553	-0.7170(-1)	right
5	0.1443	0.2378	0.1227	0.1491	1.7524(+1)	right
6	0.1977	0.1735	0.2666	0.1526	1.6284(+1)	right

local Hilbert marginal spectrum and local marginal energy spectrum are applied to reveal frequency information embedded in signals. These usefull information can be applied to CGID. Then we modeled SVM classifier to dectect the interface for coal and gangue.

Experiments results show that HHT technique has much potential in vibration signal of coal and gangue and SVM can be applied to classify the state of coal falling down with gangue effectively and accurately even in case of smaller number of samples, but HHT is more time-consuming than the traditional ones. To put into real time applications, further theoretical explantion work is needed.

ACKNOWLEDGMENT

The author would like to thank the anonymous reviewers for their valuable suggestions and comments.

REFERENCES

[1] Mowrey, G L. "Horizon control holds key to automation". *Coal*, 1992, 97(1):44-49.

[2] LIAN Z SH, LIU H J, LI W Y, "Study on the Coal Rock Interface Recognition Based on the Responses of Shearer's Cutting Force ", *Shanxi Machinery*, vol. 2, pp. 25-27, 1999.

[3] Qin J Q, ZHENG J R, ZHU X, "Coal Rock Interface Recognition Based on Natural Gamma Ray", *Colliery Mechanical & Electrical Technology*, vol. 3, pp. 9-10, 1996.

[4] WANG Z C, ZHANG X J, ZHANG H X. "The research on detection of cock content in coal rock mixture in top coal caving by natural Gamma ray". *Chinese Journal of Sensors and Actuators*, 2003, 16(4):442-446.

[5] WANG Z C. "Study on distributing coal and rock in the process of fully-mechanized coal caving technology". *Coal Mine Machinery*, 2002, 23(8):13-14.

[6] WANG Z C, WANG R L. "Research on coal seam thickness detection by natural Gamma ray in shearer horizon control". *Journal of China Coal Society*, 2002, 27(4):425-429.

[7] ZHANG J M, QIAO H B, "Coal and Rock Detection Device Based on Infrared Ray", *Mining Science & Technology*, vol.27, pp.10-11, 1999.

[8] ZHANG S X, Zhang Y L, et al. "Caved coal and rock spectrum on long-wall face". *Journal of CHINA Coal Society*, 2007, 32(9):971-974.

[9] MA R, WANG Z C. "Coal rock interface recognition based on wavelet packet transform of acoustic signal". *Coal Mine Machinery*, 2010, 31(5):43-46.

[10] N.E.Huang, S.Zheng and R L. Stenen. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis". *Proc.R.Soc.Lond.A*, pp.903-995, 1998.

[11] N.E. Huang. "Computer implicated empirical mode decomposition method, Apparatus, and article of manufacture". USA, *Provisional Application*, 5, 983, 162. Nov, 9, 1999.

[12] Huang W, Shen Z, Huang N E, et al. "Engineering analysis of Biological Variables: An example of blood pressure over one day". *Proceeding of the national academy of science*, USA, 1998, 95:4816-4821.

[13] Leisk G, Hsu N, Huang N E. "Application of the Hilbert-Huang transform to machine tool condition/health monitoring". *AIP conference proceeding*, Brunswick, 2002, 615(1):1711-1718.

[14] Chen Juan, Xu Youlin. "Application of HHT for modal parameter identification to civil structures". *Journal of Vibration Engineering*. 2003, 16(3)：383-388.

[15] Sharpley R C, Vesselin V. "Analysis of the intrinsic mode function". *Constructive Approximation*. 2006, 24:17-47.

[16] NIU F L, HUANG J, et al. "Rotor broken-bar fault diagnosis of induction motor based on Hilbert-Huang transform of the startup electromagnetic torque". *Proceedings of the CSEE*, 2005, 25(11):107-112.

[17] YU De-jie, NG Jun-Sheng, YANG Yu. "Application of Hilbert-Huang transform method to gear fault diagnosis". *Chinese Journal of Mechanical Engineering*, 2005, 41(6):102-107.

[18] DING Qi, MENG Guang, LI Hong-guang. "Beam damage identification method based on Hilbert-Huang transformation". *Journal of Vibration and Shock*, 2009, 28(9):180-183.

[19] CHERKASSKY V, MA Y Q. "Practical selection of SVM parameters and noise estimation for SVM regression". *Neural Networks*, 2004, 17(1):113-127.

[20] M. Zacksenhouse, S. Braun, M. Feldman. "Toward helicopter gearbox diagnostics from a small number of examples". *Mechanical Systems and Signal Processing*, 2000, 14(4):523-543.

[21] Hyun-Chul Kim, Shaoning Pang, Hong-Mo Je, et al. "Constructing support vector machine ensemble". *Pattern Recognition*, 2003, 36(12):2757-2767.

[22] Goudong Guo, Stan Z. Li, Kap Luk Chan. "Support vector machines for face recognition". *Image and Vision Computing*, 2001,19: 631－638.

[23] Ofir Barzilay, V.L. Brailovsky. "On domain knowledge

and feature selection using a support vector machine". *Pattern Recognition Letters*, 1999, 20 (5): 475 – 484.

[24] U. Thissen, R. Van Brakel, A.P. De Weijer, et al. "Using support vector machines for time series prediction". *Chemometricsand Intelligent Laboratory Systems*, 2003, 69 (1) :35-49.

[25] Vapnik V. "The nature of statistical learning theory". New York: *Springer-verlag*, 1999.

[26] LIU Wei, WANG Ru-lin, ZHANG Shou-xiang et al. "Real-time vibration signal acquisition of coal and rock based on DSP and ADS8509". *Coal Mine Machinery*, 2009, 30(7):187-199.

[27] LIU Wei. "Coal Rock Interface Recognition Based on Independent Component Analysis and BP Neural Network". ICCSIT2010, Vol (5), pp: 556-558.

Wei LIU received his B.S. degree in Automation from Harbin University of Science and Technology in 1999. He then went on to receive his M.S. degree in Control Theory and Control Engineering from Shenyang University of Technology. He is currently serving at Shandong Institute of Business and Technology.

His research interest covers in the area of vibration signal processing, pattern recognition and artificial intelligence recently.