Denoising of Disturbed Signal using Reconstruction Technique of EMD for Railway Bearing Condition Monitoring

Agus Susanto[1], Budi Artono[2], Surajet Khonjun[3], Rizal Mahmud[4]

**[1] Department of Railway Engineering, State Polytechnic of Madiun
East Java, 63131, Indonesia**

**[2] Department of Electrical Engineering, State Polytechnic of Madiun
East Java, 63131, Indonesia**

**[3] Department of Mechanical Engineering, Ubon Ratchathani University
Ubon Ratchathani, Thailand**

**[4] Department of Mechanical Engineering, Hiroshima University
Hiroshima, Japan**

Abstract

Railway bearing is one of the important parts which constructs boogie structure in a passenger train. This part should be monitored from bearing failure phenomena at any time for passenger safety during traveling. This study presents an effective denoising noisy signal for bearing condition monitoring. A noisy signal was created first, then separated by Empirical Mode Decomposition (EMD) to be intrinsic mode decompositions (IMFs). From IMFs, the noise can be detected, and then it was removed. Following, IMFs which contain no noise was then reconstructed to be a new signal. The Hilbert-Huang spectrum (HHT) spectrum of reconstruction signal was generated by applying Hilbert transform. HHT of the reconstruction signal was then compared to the HHT baseline spectrum and HHT contained noise. The result showed that the proposed technique works well for analyzing signals. Without reconstruction technique, the railway bearing condition was difficult to be revealed by the HHT spectrum.

Keywords: *HHT, EMD, denoising signal, HHT spectrum, bearing condition monitoring.*

1. Introduction

Railway bearing is one of the most important parts which constructs boogie structure in a passenger train. A railway bearing failure can lead to the unsafety of passengers during traveling. Therefore bearing condition monitoring at any time is one of the important tasks.

Bearing condition monitoring generally can be divided into two fundamental methods. The first is the direct method. This approach is including the use of optical and vision, which has the benefit of capturing the actual geometric changes of bearing during operation. Unfortunately, this method is difficult to be applied in real conditions. The reason is needed the complex additional feature for setup those devices [1]. Second is the indirect method. The vibrations [2], [3], sound [4], [5], and acoustic emissions signal [6] are common signals which measured in the observed system to monitor the bearing condition. Besides, for analyzing those kinds of signals, fast Fourier transform (FFT) is commonly employed for monitoring in frequency spectrum [7], [8], [9]. In this method, a signal is measured during operation, and the signal is then processed using any signal processing technique. However, FFT contains the weakness which is impossible to be applied for processing the transient signal. Because the transient signal is typically nonlinear and non-stationary signal. On the other hand, the real process is described as a nonlinear and non-stationary process [10]. Besides, FFT provides feature results only in the frequency domain. It is another weakness of FFT.

Time-frequency analysis (TFA) methods have a great potential benefit to detect the failure of bearing condition. Because the methods can map time-domain signal into a two-dimensional plane, namely the time-frequency domain. It means that this method can be used to monitor the bearing condition in both time and also the frequency at one time. The TFA methods are being developed and used in bearing condition monitoring recently, such as short-time Fourier transform [11], [12], Wavelet transforms [13],

IJCSI International Journal of Computer Science Issues, Volume 17, Issue 5, September 2020
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org https://doi.org/10.5281/zenodo.4418876

[14], and Stockwell transforms [15]. However, these methods are blind to transient signal processing.

Hilbert–Huang transform (HHT) is appropriate for processing the signal obtained in the real system process. It is suitable for transient vibration. Authors have been successfully applied HHT to process signal obtained in machining application [16], [17], [18], [19], [20]. In this research, they used HHT for chatter detection in milling and turning processes.

Even though HHT is a powerful method for TFA, the presence of noise still disturbs the analysis, especially the noise that will disturb the HHT spectrum. Denoising technique to reduce noise from the noisy signal may improve the performance of HHT. However, general filters is constrained to eliminate the noise effectively [21]. Empirical Mode Process (EMD) process is the first step of HHT, which can be employed for reducing noise from a noisy signal. It may be a good way before generating the HHT spectrum after Hilbert transform applied.

In this paper, the reconstruction technique by EMD is introduced for reducing noise from noisy signals in order to monitor the bearing condition. The signals are first decomposed by the EMD process to get a set of intrinsic mode function (IMF) components. From IMF components, the noisy signal can be detected and then removed from the clear signal. All IMFs which clear from noise are then reconstructed to be processed in the next step.

2. Method

There are two major steps in the Hilbert-Huang Transform (HHT), namely Empirical Mode Decomposition (EMD) process and Hilbert transform. These steps should be done consecutively.

2.1 Empirical Mode Decomposition Process

The complex signal is spelled out into a simple oscillation by EMD, which is called as IMFs and a monotonic residue. An example of IMF components is shown in **Fig. 1.** From this figure, C1 – C12 are the IMF components and the monotonic residue is provided in the last panel. As can be seen, the signal is arranged from the high frequency in the first IMF and low frequency in the last IMF.

2.2 Hilbert Transform

Hilbert transform is then applied for each IMF to generate the HHT spectrum of the signal. **Figure 2** displays an example of the HHT spectrum**.** From this spectrum, HHT provides spectrum with high resolution and we can detect any mechanical process, for instant bearing condition monitoring, in time and frequency domain using this spectrum.

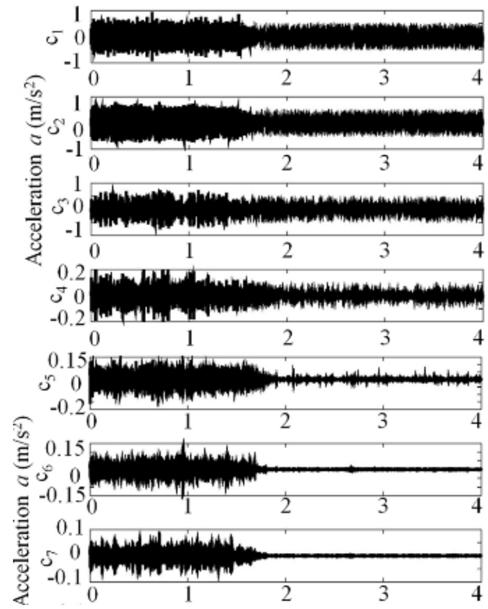


Fig. 1 IMF component obtained by EMD [18].

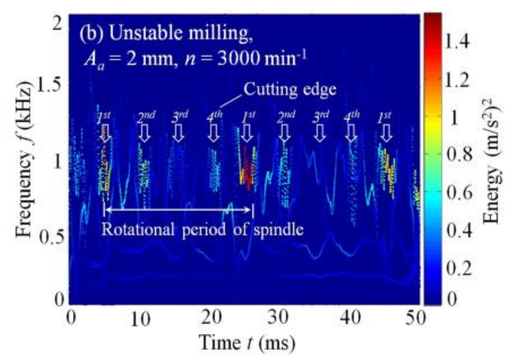


Fig. 2 HHT spectrum obtained by Hilbert transform [18].

The task of bearing condition monitoring is to find out the anomaly frequencies from the measured signals during operation. However, the measured signals are usually contaminated by the noise during the machining process. The removal of noise is so much important for the correct feature extraction of the measured signal.

This study presents an effective method of denoising noisy signals for bearing condition monitoring by means analyzing the synthetic vibration signals. First, a clear signal was created as

$$x(t) = 6\sin(2\pi\omega_1 t) + 1.5\sin(2\pi\omega_2 t) + 2.5\sin(2\pi\omega_3 t) \quad (1)$$

where t is the time interval, and ω is the signal frequency which set to be ω_1 = 20 Hz, ω_2 = 40 Hz, and ω_3 = 60 Hz, respectively.

The synthetic signal in the Eq. (1) is used for the baseline signal and it is displayed as shown in Fig. 3.

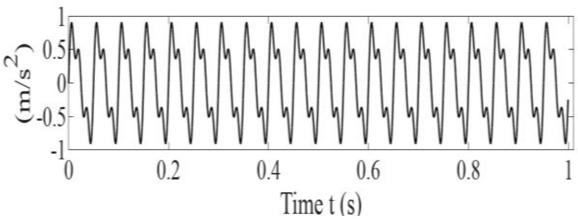


Fig. 3 Time domain of clear vibration signal.

Second, the noisy synthetic signal was created by adding signal noise into the clear signal mentioned in Eq. (1). The noisy signal is set as

$$noise(t) = \sin(2\pi 500 t) \quad (2)$$

From Eq. (2), the noise frequency is 500 Hz and it is displayed as follow;

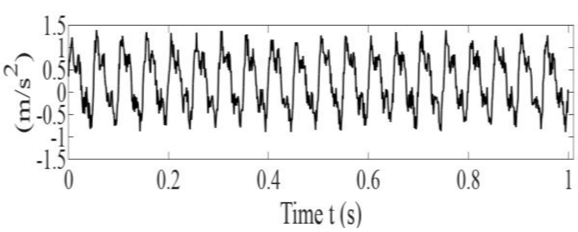


Fig. 4 Synthetic noise signal.

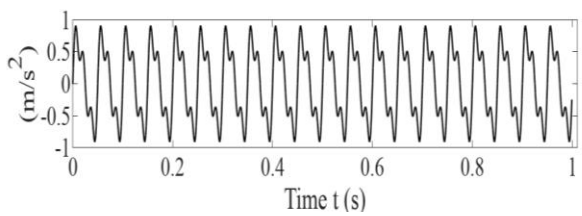
Following, HHT is applied onto a noisy synthetic signal. The first step of HHT is applying EMD to separate the noisy synthetic signal to be intrinsic mode decompositions (IMFs). From IMFs, the noise can be detected, and then it was removed. Following, IMFs which contain no noise was then reconstructed to be a new signal. Hilbert transform is then applied to the clear, noisy, and new signals to generate the HHT spectrum.

3. Result and Discussion

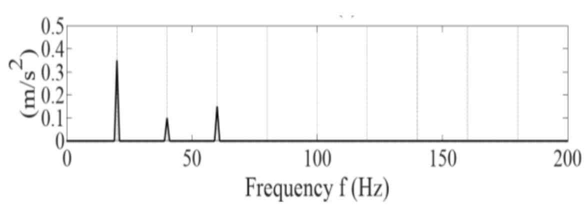
3.1 Synthetic Signal in Time Domain and Its Frequency Spectrum

To confirm the proposed method, two synthetic signals are generated in this section. First is a clear signal as shown in **Fig. 5(a).** This signal is used for baseline signals in our discussion and represents the vibration without noise measured during operation. From the figure, the vibration is clear and no noise disturb the signal.

Let us investigate the frequency content of this vibration signal by its frequency spectrum. The frequency spectrum of this signal is shown in **Fig. 5(b).** This spectrum was calculated by fast Fourier transform (FFT). As shown in the figure, the spectrum consists of spindle rotational frequency (20 Hz) which is associated with spindle rotation of 1200 rpm. Besides, the harmonic frequencies of the rotational railway axle (40 and 60 Hz) can also be observed in this spectrum, which was multiplying the f_{axle} frequency. These frequencies are well-known as the characteristic frequency of bearing.



(a) Time-domain of clear vibration signal.

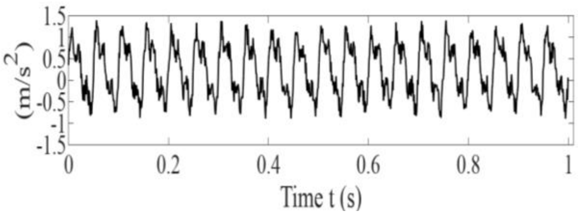


(b) Frequency spectrum of clear vibration signal.

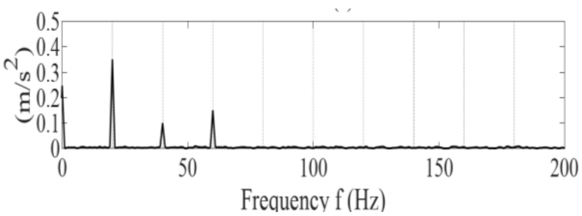
Fig. 5 Clear vibration signal.

Second is the noisy signal as shown in **Fig. 6(a).** This noisy signal was generated by added the clear signal shown in **Fig. 3** with the synthetic noise signal in **Fig. 4**. This signal represents the vibration with noise measured during operation. It can be seen that the vibration is similar to the clear signal, but some noises disturb the signal. Therefore, the signal is distorted by noise. This signal is generally obtained in real measurements of any system.
Let us investigate the frequency content of this vibration signal by FFT. And the result is shown in **Fig. 6(b)**. Here,

the spectrum also consists of some frequency same as in **Fig. 3(b)**, namely; spindle rotational frequency (20 Hz) which is associated with spindle rotation of 1200 rpm and its harmonic frequencies (40 and 60 Hz). Unfortunately, the frequency spectrum is distorted by noise. As the result, the figure provides not a smooth spectrum.



(a) Time-domain of clear vibration signal.



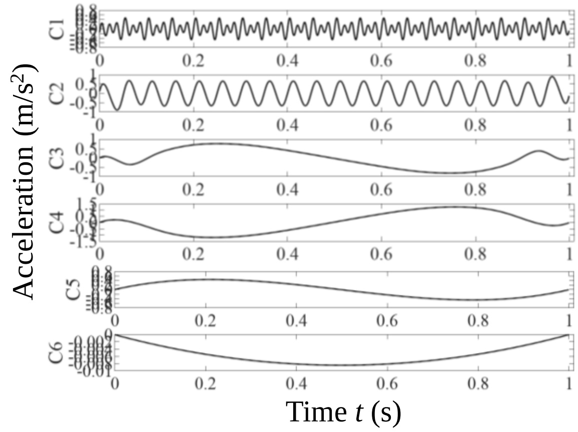
(b) Frequency spectrum of noisy vibration signal.

Fig. 6 Noisy vibration signal.

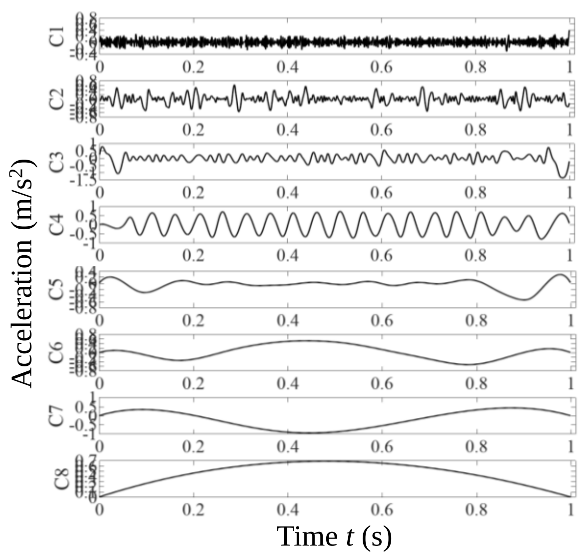
3.2. Vibration analysis using HHT

The vibration signals are shown in **Figs. 5(a)** and **6(a)** then preprocessed by EMD first to get a set of IMF components. The IMF components of clear and noisy signals are shown in **Figs. 7(a)** and **7(b)**, respectively. EMD produces six IMF components in **Fig. 5(a)** and **Fig. 5(b)** produces eight IMF components. C1 to C5 of **Fig. 7(a)** are components IMF1 to IMF5 correspond to clear signal, and C1 to C7 of **Fig. 5(b)** are components IMF1 to IMF7 correspond to noisy signal. On the other hand, C6 and C8 are the monotonic residues of the EMD process for each case. Now let us investigate the frequency content of each IMF by FFT to find the exact reason why noisy signals produced eight IMFs and different from the clear signal.

The frequency spectra that correspond to all IMF components for each case are shown in **Fig. 8.** According to **Fig. 8(a)**, IMF 1 and IMF 2 have significant vibration of the observed signal because they contained characteristic frequencies. IMF 1 consists of harmonic frequencies (40, 60 Hz). IMF 2 consists of spindle rotational frequency (20 Hz). On the other hand, IMF 3 and IMF 4 have significant vibration of the observed noisy signal. They are consisting of spindle rotational, and its harmonic frequencies. Besides, IMF 1 and IMF 2 contain signal noise. Therefore, the presence of noise caused two additional IMFs in the case (b). It needs to be noted that the EMD can separate the clear signal from noise. It means that the EMD process can be used for filtering messy signals caused by noise. We will discuss it later in the following sub-chapter; denoising signal using reconstruction technique by EMD.

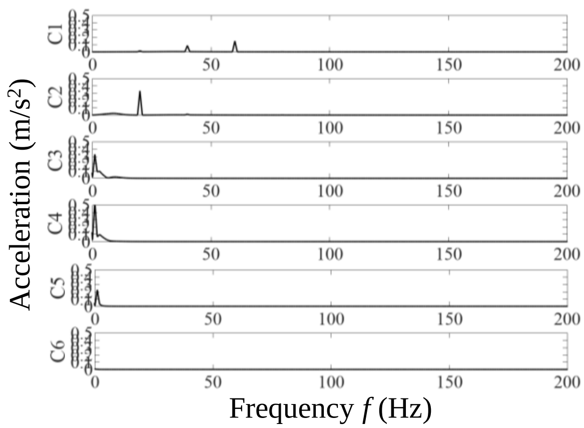


(a) IMF components correspond to clear signal.

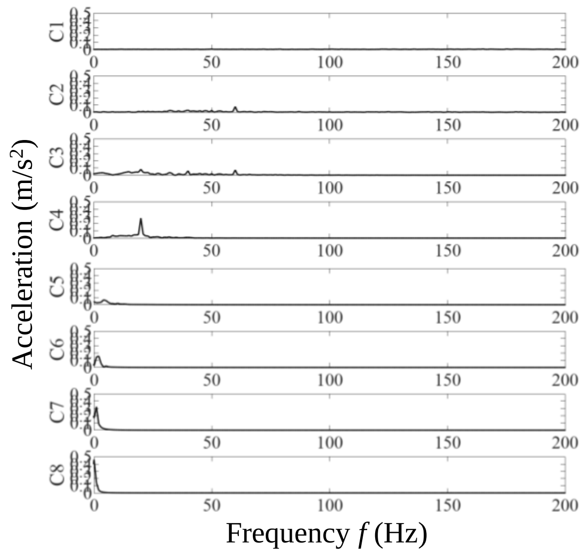


(b) IMF components correspond to noisy signal.

Fig. 7 IMF components in time domain obtained by EMD process.



(a) Frequency spectrum of IMF components for clear signal.

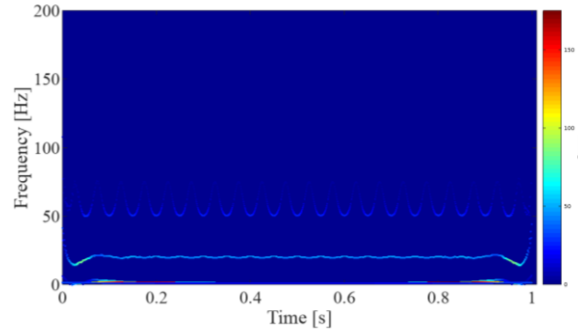


(b) Frequency spectrum of IMF components for noisy signal.

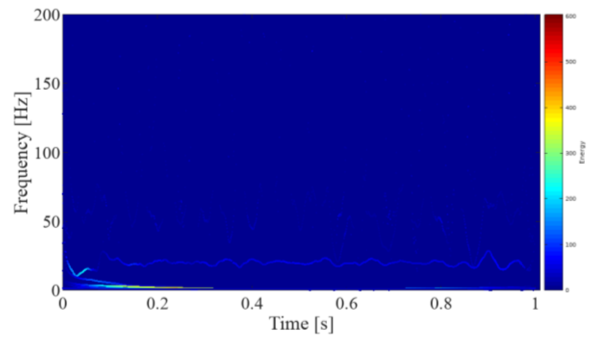
Fig. 8 IMF components in frequency domain.

The second step of HHT is applying the Hilbert transform to generate the HHT spectrum. The HHT spectra of each vibration signal are shown in **Fig. 9. Figure 9(a)** represents the HHT spectrum of a clear signal. As mentioned before that this signal is used for baseline data. It can be seen that the energy gathers in line with certain frequency components, namely, spindle rotational frequency and harmonic of tooth passing frequency. Besides, **Fig. 9(b)** is the HHT spectrum correspond to the noisy signal. As can be seen from the figure, the energy is messy and higher than the HHT spectrum of **Fig. 9(a)**. Besides, there is no characteristic frequency component which can be found in this spectrum like the spectrum in **Fig. 9(a)**. Thus, the noise was also disturbing the spectra when HHT is employed for bearing condition monitoring.

To fix this problem, the EMD process will be used for denoising signals by reconstruction technique.



(a) HHT spectrum corresponds to clear signal.



(b) HHT spectrum correspond to noisy signal.

Fig. 9 HHT spectra obtained by Hilbert transform.

3.3 Denoising signal using reconstruction technique by EMD

In this discussion, the reconstruction technique by EMD for the de-noise noisy signal. In this way, we have to remove IMF 1 and IMF 2 of **Fig. 7(b)** for the reconstruction technique, because they were the noise signals as explained in the previous discussion.

The sequence steps of the reconstruction IMFs are displayed in **Fig 10**. In each of the sub-panels, it has been plotted the original signal as a black curve and the partial summing of the IMFs as a red curve. **Figure 10** displays for synthetic noisy signals in case (b), meanwhile clear signal (case a) can be produced in the same way.

IJCSI International Journal of Computer Science Issues, Volume 17, Issue 5, September 2020
ISSN (Print): 1694-0814 | ISSN (Online): 1694-0784
www.IJCSI.org https://doi.org/10.5281/zenodo.4418876

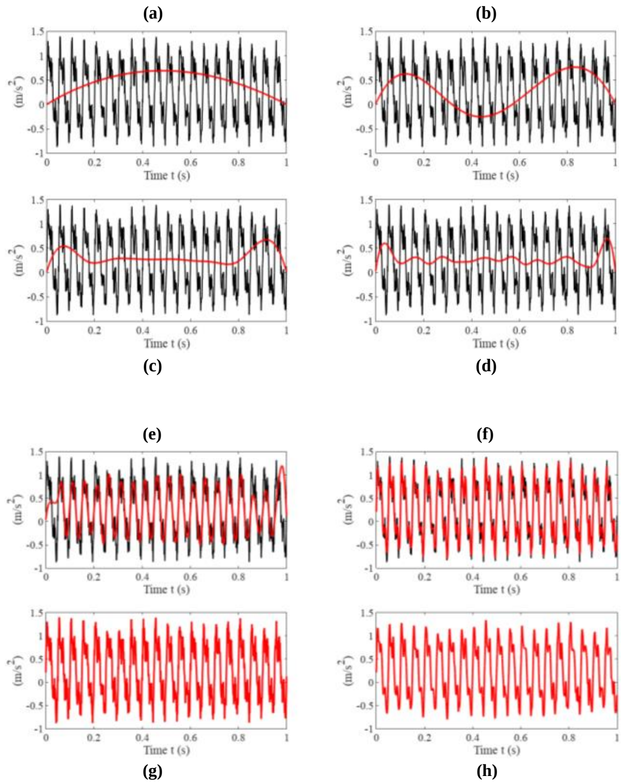


Fig. 10 Reconstruction signal of IMF components. Black curve is original signal and red curve is reconstruction IMFs.

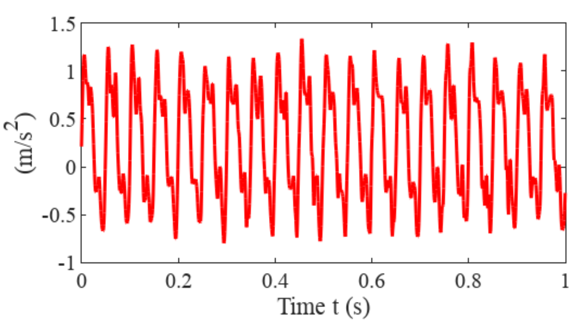


Fig. 11 Time domain of reconstruction signal.

Figure 10(a) is plotting the monotonic residue (C8) onto original signal. This certainly is not a significant trend because the vibration amplitude of monotonic residue as small as shown in the last sub-panel of **Fig. 7(b)**. When the monotonic residue (C8) was added with IMF 7, then **Fig. 10(b)** has resulted. When the monotonic residue (C8) was added with C7, C6, C5, C4, and C3, then **Fig. 10(f)** has resulted. These curves provide the smoothest trend of the data variation. With step by step adding of the IMF components, we finally arrive at the summing of all the IMF components shown in **Fig. 10(g)**. It looks like the baseline vibration signal in **Fig. 5(a)**. This reconstruction signal means filtered signal and it is shown in **Fig. 11**. This reconstruction procedure the utility of the EMD process as a data filter. If we stop at any step, we would have the trend of the vibration process.

In order to demonstrate the efficiency of the EMD process as the filter data, the HHT spectrum of reconstruction signal was provided as shown in **Fig. 12.** This HHT spectrum is quite similar to the baseline spectrum shown in **Fig. 9(a)**. After de-noise using the reconstruction technique of EMD, the energy now gathers in line of certain frequency components clearly, namely spindle rotational frequency and its harmonic frequency even though did not perfect as HHT spectrum of **Fig. 7(a).**

It means that HHT works well with the reconstruction technique for bearing condition monitoring. It can be seen that HHT after denoising the signal using the reconstruction technique works well than HHT without denoising the signal using the reconstruction technique for bearing condition monitoring.

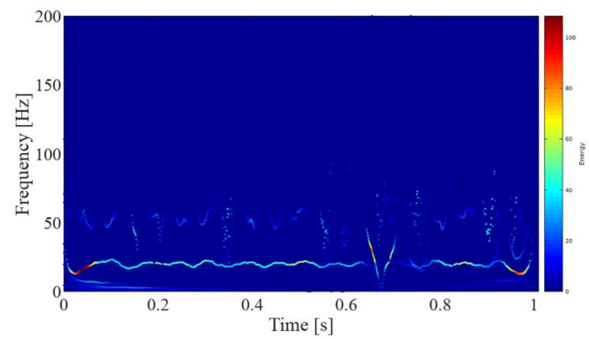


Fig. 12 HHT spectrum correspond to reconstruction signal.

4. Conclusions

In this paper, railway bearing condition monitoring was studied using Hilbert-Huang Transform (HHT) by mean analyzing the synthetic vibration signals. To improve the performance of HHT, denoising signal using reconstruction technique for data filter and HHT spectrum was obtained, and the results have shown that:

(a). The complex signal can be decomposed by the EMD process to be IMF components.

(b). Noise can be detected based on IMFs. In our case C1 and C4 of the case (b) are noise.

(c). EMD can be used for data filter by reconstruction data technique.

HHT with the denoising signal using reconstruction technique works well efficiently than HHT without denoising signal using reconstruction technique for bearing condition monitoring

Acknowledgments

The authors wish to thank the Ministry of Research and Technology (Now is the Ministry of Education and Culture), Indonesia for supporting a grant (No. B/87/E3/RA.00/2020).

References

[1] K. P. Zhu, Y. S. Wong, and G. S. Hong, "Wavelet Analysis of Sensor Signals for Tool Condition Monitoring: A Review and Some New Results", Int. J. Mach. Tools Manuf., Vol. 49, No. 7–8, 2009, pp. 537–553.
[2] B. Huang, W. Xu, and X. Zou, "Rolling Bearing Diagnosis Based on LMD and Neural Network", Int. Journal of Computer Science Issues, Vol. 10, Issue 1, No 3, 2013, pp. 304-309.
[3] J. Lin, "Improved Ensemble Empirical Mode Decomposition and its Applications to Gearbox Fault Signal Processing", Int. Journal of Computer Science Issues, Vol. 9, Issue 6, No 2, pp. 194-199, 2012.
[4] S. Lu, P. Zheng, Y. Liu, Z. Cao, H. Yang, and Q. Wang, "Sound-Aided Vibration Weak Signal Enhancement for Bearing Fault Detection by Using Adaptive Stochastic Resonance", J. Sound Vib., Vol. 449, 2019, pp. 18–29.
[5] X. T. Bai, Y. H. Wu, I. C. Rosca, K. Zhang, and H. T. Shi, "Investigation On the Effects of the Ball Diameter Difference in the Sound Radiation of Full Ceramic Bearings", J. Sound Vib., vol. 450, 2019, pp. 231–250.
[6] B. S. Kim, D. S. Gu, J. G. Kim, Y. C. Kim, and B. K. Choi, "Rolinig Element Bearing Fault Detection using Acoustic Emission Signal Analyzed by Envelope Analysis with Discrete Wavelet Transform," in The 4th World Congress on Engineering Asset Management (WCEAM), 2009, pp. 596–602.
[7] Y. Chen, H. Jiang, "Research and Application of BSS Algorithm on the Gearbox Fault Diagnosis Based on the MMI Criterion", Int. Journal of Computer Science Issues, Vol. 10, Issue 1, No 1, 2013, pp. 222-225.
[8] H. Khammari, "A New Spectral Based Characterization of Electrocardiogram Signals in Sudden Cardiac Death", Int. Journal of Computer Science Issues, Vol. 9, Issue 1, No 2, 2012, 193-201.
[9] K. Muludi, Aristoteles, and A. F. SFB. Loupatty, "Identification Chord Identification Using Pitch Class Profile Method with Using Pitch Class Profile Method with Fast Fourier Transform Feature Extraction", Int. Journal of Computer Science Issues, Vol. 11, Issue 3, No 1, 2014, pp. 139-144.
[10] N. E. Huang and S. S. P. Shen, Hilbert–Huang Transform and Its Applications, Singapore: World Scientific Publishing, 2005.
[11] H. Liu, L. Li, and J. Ma, "Rolling Bearing Fault Diagnosis Based on STFT-Deep Learning and Sound Signals," Shock Vib., Vol. 2016, 2016, pp. 1–12.
[12] M. Rusli, L. Son, M. Bur, and A. Arisman, "Application of Short Time Fourier Transform and Wavelet Transform for Sound Source Localization Using Single Moving Microphone in Machine Condition Monitoring," in ICoSE Conference on Instrumentation, Environment and Renewable Energy, 2016, pp. 1–6.
[13] Z. Gao, J. Lin, X. Wang, and X. Xu, "Bearing Fault Detection Based on Empirical Wavelet Transform and Correlated Kurtosis by Acoustic Emission", Materials, Vol. 10, No. 6, 2017, p. 571.
[14] Z. Yang, U. C. Merrild, M. T. Runge, G. K. M. Pedersen, and H. Børsting, "Application of a New EWT-based Denoising Technique in Bearing Fault Diagnosis," in 7th IFAC Symposium on Fault Detection, Supervision and Safety of Technical Processes, 2009.
[15] J. Cai and Y. Xiao, "Time-frequency Analysis Method of Bearing Fault Diagnosis Based on the Generalized S Transformation," J. Vibroengineering, vol. 19, no. 6, 2017, pp. 4221–4230.
[16] A. Susanto, K. Yamada, R. Tanaka, Y. A. Handoko, and M. F. Subhan, "Chatter identification in turning process based on vibration analysis using Hilbert- Huang transform," J. Mech. Eng. Sci., Vol. 14, No. 2, 2020.
[17] A. Susanto, C.-H. Liu, K. Yamada, Y.-R. Hwang, R. Tanaka, and K. Sekiya, "Milling Process Monitoring Based on Vibration Analysis Using Hilbert-Huang Transform," Int. J. Autom. Technol., Vol. 12, No. 5, 2018, pp. 688–698.
[18] A. Susanto, C. H. Liu, K. Yamada, Y. R. Hwang, R. Tanaka, and K. Sekiya, "Application of Hilbert–Huang transform for vibration signal analysis in end-milling," Precision Engineering, Vol. 53, 2018, pp. 263–277.
[19] A. Susanto, K. Yamada, K. Mani, R. Tanaka, and K. Sekiya, "Vibration Analysis in Milling of Thin-Walled Workpieces Using Hilbert-Huang Transform," in 9th Int. Conference on Leading Edge Manufacturing in 21st century : LEM21, 2017, vol. 9, pp. 1–6.
[20] A. Susanto, K. Yamada, R. Tanaka, M. Azka, M. P. Sekiya, and P. Novia, "Analysis of Transient Signal using Hilbert-Huang Transform for Chatter Monitoring in Turning Process," in The 4th Int. Conference on Information Technology, Information Systems and Electrical Engineering, 2019, vol. 2019, pp. 26–30.
[21] H. Cao, Y. Lei, and Z. He, "Chatter identification in end milling process using wavelet packets and Hilbert-Huang transform," Int. J. Mach. Tools Manuf., Vol. 69, 2013, pp. 11–19.

Dr. Eng. Agus Susanto holds his doctor's degree from Dept. of Mechanical Systems Engineering, Hiroshima Univ., Japan. He currently is one of the lecturer staff at the Department of Railway Engineering, State Polytechnic of Madiun. His main research interesting is the Application of Hilbert–Huang transform for vibration signal analysis in end-milling (Published in Precision Engineering, 2018), Milling Process Monitoring Based on Vibration Analysis Using Hilbert-Huang Transform (Int. J. of Automation Technology, 2018); Chatter identification in turning process based on vibration analysis using Hilbert-Huang Transform (J. of Mechanical Engineering and Sciences (JMES), 2019). He

received an award as the young researcher from Japan Society for Precision Engineering (JSPE), 2019.

Budi Artono is currently a lecturer staff in the Department of Electric Engineering at State Polytechnic of Madiun, Indonesia.

Surajet Khonjun, Ph.D. in Eng. is a professional lecturer staff at the Department of Mechanical Engineering, Ubon Ratchathani University, Thailand. He received his doctoral degree from the Department of Mechanical Systems Engineering, Hiroshima University. His research interesting is about the machining process.

Rizal Mahmud Ph.D. in Eng. is currently studying post-doctor in Dept. of Mechanical Systems Engineering, Hiroshima Univ., Japan. Besides, he is a lecturer staff in the Dept. of Mechanical Engineering at Adhitama Institute of Technology, Surabaya, Indonesia.