Radiation Physics and Chemistry 149 (2018) 49–53

Contents lists available at ScienceDirect

Radiation Physics and Chemistry

journal homepage: www.elsevier.com/locate/radphyschem

Noise reduction of PGNAA spectrum using empirical mode decomposition technique

E. Bayat[a,b], H. Afarideh[b,*], F. Abbasi Davani[c], N. Ghal–Eh[d,e]

[a] Nuclear Science and Technology Research Center, AEOI, Tehran, Iran
[b] Department of Energy Engineering and Physics, Amir Kabir University of Technology, Tehran, Iran
[c] Radiation Application Department, Shahid Beheshti University, Tehran, Iran
[d] School of Physics, Damghan University, Damghan, Iran
[e] Department of Physics, School of Sciences, Ferdowsi University of Mashhad, Mashhad, Iran

ARTICLE INFO

PACS:
28.41.Rc
29.40.Mc
29.85.–c

Keywords:
Material analysis
PGNAA
Noise reduction
Wavelet method
EMD technique

ABSTRACT

Prompt gamma neutron activation analysis (PGNAA) is frequently used in on–line analysis of raw materials in cement and coal industries which normally incorporates bismuth germanate (BGO) or sodium iodide (NaI(Tl)) scintillators. The quantitative results are basically undertaken through full–spectrum analysis method which requires an efficient noise reduction procedure to optimize PGNAA data. Here in this study, the empirical mode decomposition (EMD) technique has been used to reduce the noise level of PGNAA spectra of a neutron–irradiated $NaCl{\cdot}H_2O$ solution and then the results have been compared with those of wavelet technique. The mean square errors (MSEs) comparisons confirm that both EMD and wavelet techniques can be efficiently used for noise reduction purposes, however, this study recommends the EMD technique for its independency of basic functions, simplicity and spectrum data-based operation.

1. Introduction

PGNAA has been extensively used in various applications such as explosive and drug identifications in passenger luggage, landmine detection, separation of chemical from non–chemical explosives in old remnants of wars, cement and coal industries, etc. (Oden et al., 2006; Charbucinski et al., 2003; Lim and Abernethy, 2005; Gozani and Strellis, 2007; Bergaoui et al., 2014). The PGNAA gamma ray spectrum may be analyzed either through peak search or full spectrum. The peak search method is generally implemented in case of high–resolution detector such as high–purity germanium (HPGe) where the qualitative and quantitative studies are undertaken according to the position and area under a specific peak. The full–spectrum method, on the other hand, is popular in case of relatively poor–resolution detectors such as BGO or NaI(Tl) scintillators (Ghal-Eh et al., 2016). In full–spectrum method, the gamma–ray spectra corresponding to specific amounts of all elements of interest are obtained either through measurement or simulation to form spectrum libraries. Then the unknown sample spectrum which is assumed to be a linear superposition of library spectra is unfolded with one of the several mathematical methods such as least–squares (Gardner and Xu, 2009), fixed–point iterations (Akkurt, 2002), artificial neural networks (Doostmohammadi et al., 2010), etc., leading to quantitative and qualitative elemental data.

This analysis method has been commonly used in commercial PGNAA systems such as those used in on–line coal and cement raw material analysis. The full–spectrum analysis is unfortunately an inverse–problem type in which there may be numerous solutions for a single input condition. An inverse problem is actually the process of calculating the causal factors of a set of observations (e.g., calculating an image in X-ray computed tomography from detectors data). It is called an inverse problem because it starts with the results and then calculates the causes. This is the inverse of a forward problem, which starts with the causes and then calculates the results (Tarantola, 2005).

Therefore, in order to improve the precision of this method, one has to reduce the noise in gamma ray spectrum in addition to appropriate boundary condition determination. The gamma ray spectrum noise may be attributed mainly to low counting statistics which is itself due to short spectroscopy time, low detection efficiency at high–energy region of spectrum (e.g., 10.8 MeV nitrogen peak) or the small sample activity. The statistical noise of gamma ray spectrum normally decreases after a very long acquisition time but since this is not applicable in most cases one has to use computational methods for filtration and noise reduction. Filtration for noise reduction is used in many science and engineering disciplines. Well known filtration techniques such as FT,

* Corresponding author.
E-mail address: hafarideh@aut.ac.ir (H. Afarideh).

https://doi.org/10.1016/j.radphyschem.2018.01.015
Received 14 May 2016; Received in revised form 30 October 2017; Accepted 16 January 2018

STFT, wavelet and PCA depending on signal characteristics (i.e., stationary or non–stationary, linearity or non–linearity, etc.) may be used in time, frequency or time–frequency domains.

Since the PGNAA spectrum is of non–stationary nature, there are very limited number of noise reduction techniques (e.g., wavelet) proposed for this purpose (Barzilov et al., 2015). Although the wavelet method represents a relatively appropriate time–frequency resolution, the choice of basic function determines the accuracy of this method which is not always an easy task (Martis et al., 2011; Singh and Tiwari, 2006).

The EMD technique was first presented by Huang in 1998 (Huang et al., 1998). The validity of this method in non–stationary and even non–linear signal analysis has been proved. EMD is totally adaptive and data driven and it does not require basic function selection. In this method, a non–stationary non–linear signal is decomposed into a stationary linear component of intrinsic mode function (IMF) together with a remainder (i.e., a constant value or signal trend) such that the original signal can be completely reconstructed with these components. Therefore, high–frequency components (i.e., noise) can be simply discriminated from main data (Boudraa et al., 2007; Tsolis and Xenos, 2011). The EMD techniques has been used in signal analysis and classification as well as noise reduction in biomedical engineering, seismology, mechanical engineering, optics, etc. (Colominas et al., 2014; Rojas et al., 2013; Su et al., 2010; Wang et al., 2012; Yin et al., 2015).

In this research, EMD has been used for the noise reduction of an NaI(Tl) spectrum when exposed to prompt gamma rays of a neutron–activated sample. The results have been compared with wavelet output data to show the feasibility of the proposed method.

2. Materials and methods

2.1. PGNAA measurement setup

The prompt gamma spectrum of a neutron–activated sample has been measured with a portable PGNAA tool as shown in Fig. 1. The setup has been located at 95 cm and 200 cm distances from the laboratory ground and surrounding walls, respectively. The setup consists of a 10 mCi ^{252}Cf neutron source, a Scionix 3–inch by 3–inch right cylinder NaI(Tl) scintillator, a NIM–standard spectroscopy electronics and appropriate detector shielding.

The shielding consisting 18.5 cm iron followed by 31.5 cm high–density polyethylene (HDPE) has been constructed in such a way that the thermal neutron fluence at sample position is optimized (Bayat et al., 2016). In order to suppress the background count rate, the NaI (Tl) detector has been placed inside a 2.5 cm thick lead shield. The sample has been 400 g NaCl dissolved in 4 l H_2O.

The gamma–ray spectra has been measured with a 13–bit (or equivalently, 8192–channel) analog–to–digital convertor (ADC) to intentionally enhance the noise contribution.

The noisy and reference PGNAA spectra of the sample have been measured in 600 s and 15 h, respectively. In order to balance the spectroscopy time with the contribution of delayed gamma rays originating from sample, detector and shielding elements, the long

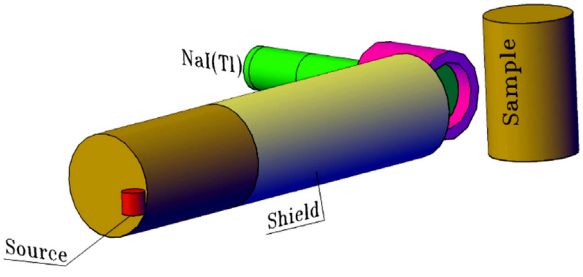

Fig. 1. Schematics of a portable PGNAA measurement system.

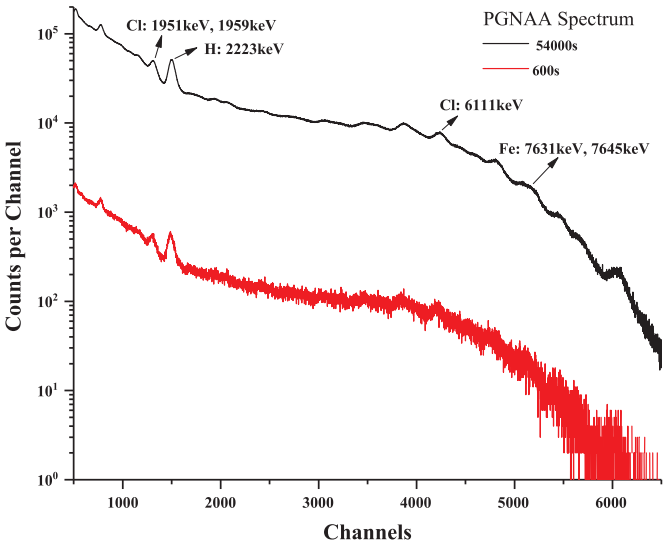

Fig. 2. Neutron–activated prompt (and delayed) gamma rays spectra of NaCl·H_2O solution measured in two different live times (600 s and 15 h).

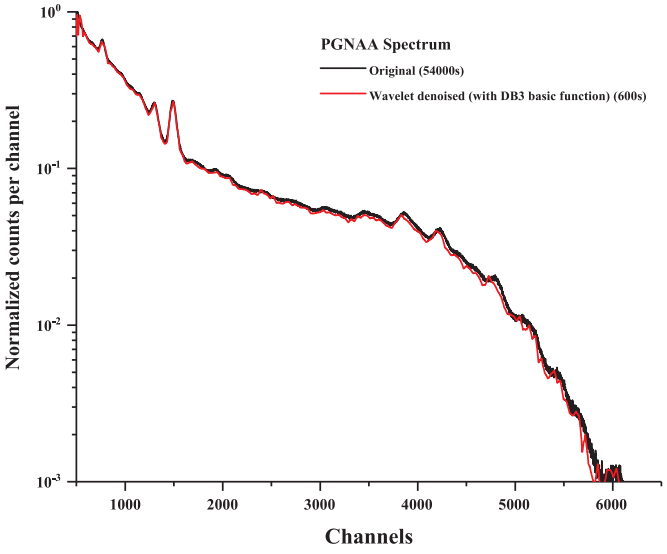

Fig. 3. Comparison between denoised prompt gamma ray spectrum using wavelet method (with DB3 basic function) and reference spectrum.

acquisition has been undertaken prior to the short one. The low–amplitude pulse height region of PGNAA spectrum includes many peaks associated with prompt and delayed characteristic gamma rays, as well as single– and double–escape peaks corresponding to higher–energy gammas. The background gamma–rays, almost all Compton continua, backscattering peaks, electronic noise and the dark current of photomultiplier tube (PMT), etc. also contribute in small pulse height region. This clearly causes a high counting rate and consequently large dead time.

This pulse–height region of PGNAA spectrum would not provide useful information if poor resolution detectors such as NaI(Tl) scintillator are used which is due to many peak overlaps. This also perturbs the full spectrum analysis such that a small variation in high–energy region would not result in an observable effect which weakens the analysis sensitivity. In full spectrum analysis, depending on the elemental characteristic gamma rays, the low pulse–height region is omitted as much as possible. In this research, the PGNAA spectrum of neutron–activated NaCl.H_2O solution below 700 keV is omitted because the sodium and chlorine characteristic gamma rays are (1368 keV, 2027 keV, 2754 keV, …) and (789 keV, 1164 keV, 1951 keV, 1959 keV,

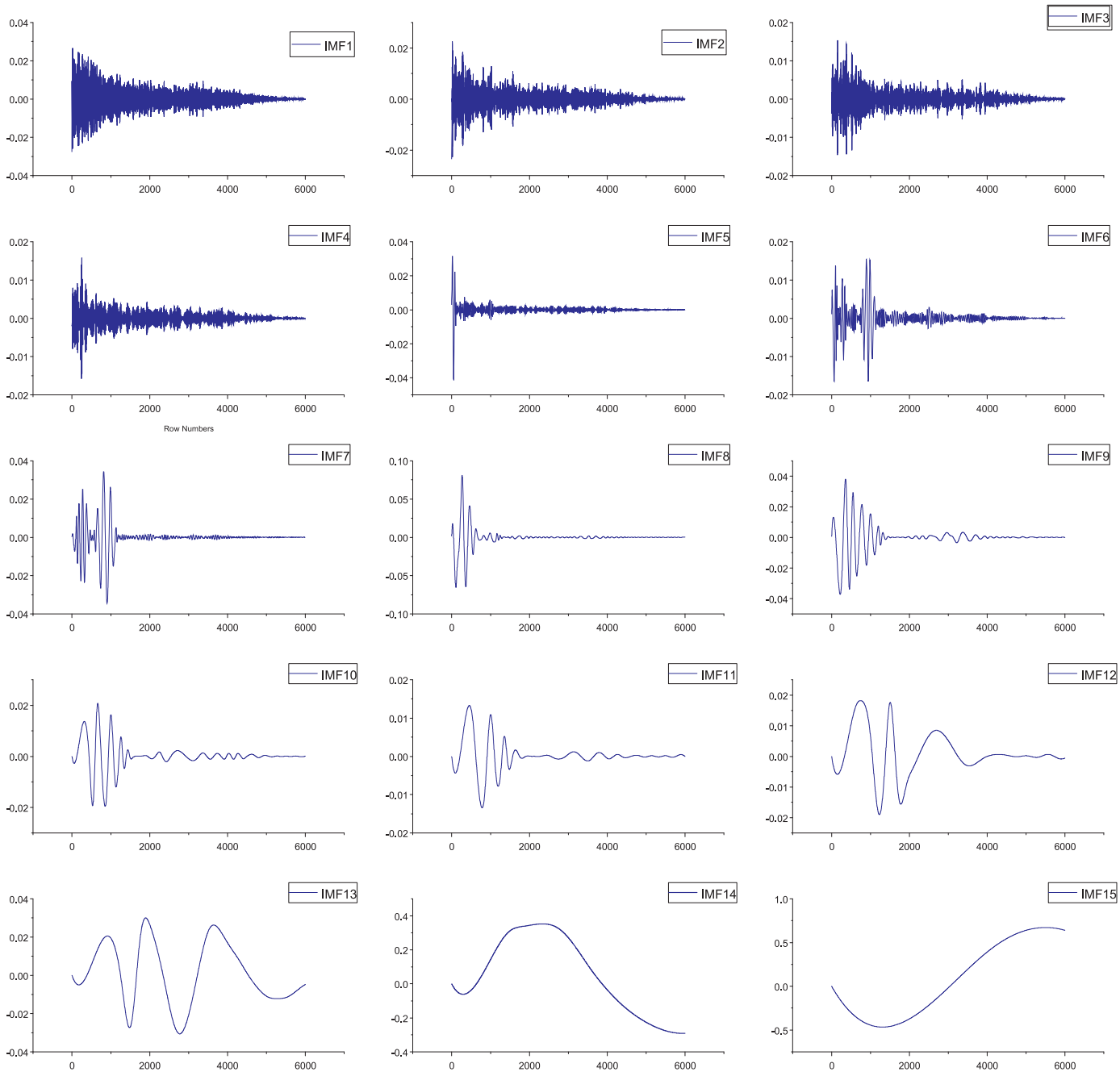

Fig. 4. S(x) spectrum decomposed into IMFs using EMD algorithm.

6111 keV), respectively (see Fig. 2).

In order to dismiss the low-amplitude region of spectrum (i.e., the region associated with both low-energy gamma rays and low-amplitude electronic noises), it has been decided to set the lower level discriminator (LLD) of the ADC at about channel number 400. This actually ignores the first 400 channels which are corresponding to an energy range of 0 to about 700 keV. The sudden jump at channel number 401 normally disturbs the noise reduction procedures. To fix this problem, one has to shift the channel number 400 to the origin, however, the noise reduction procedure remains unaffected following this change.

2.2. Noise reduction implementation procedure

Both the reference and short–time spectra are normalized to lie within 0 and 1. The noise–reduction techniques have been performed on normalized short–time spectrum and then it has been compared with the normalized reference spectrum simply through visual observation. Then the mean squared error (MSE) factor is calculated to estimate the noise reduction quality as follows:

$$MSE = \frac{\sum_{t=0}^{L-1} (R(x) - S_n(x))^2}{L} \quad (1)$$

Where R(x), $S_n(x)$ and L are normalized reference spectrum, noised–reduced normalized short–time spectrum and number of channels, respectively. The L value in denominator may be ignored as the number of channels in reference spectrum and all noise–reduced spectra are the same. Clearly, smaller MSE corresponds to more efficient noise reduction.

The noise reduction using wavelet has been performed with Origin software (Originlab, 2017). Using Origin, the main basic functions

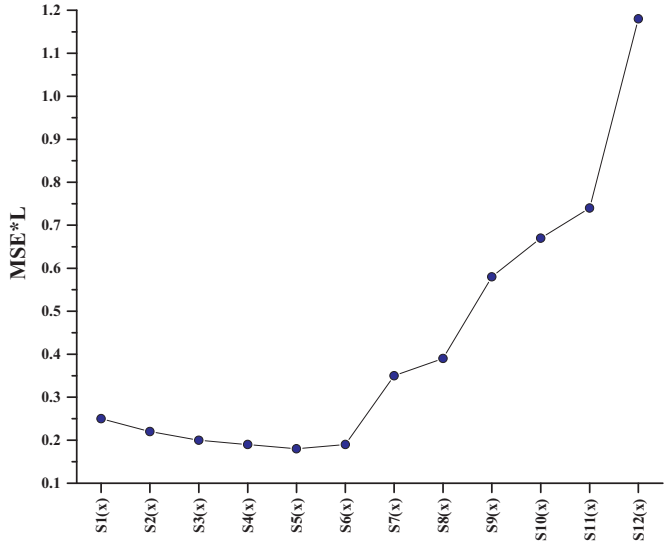

Fig. 5. The sum squared error (MSE × L) calculated for subtractions of different number of IMFs from S(x).

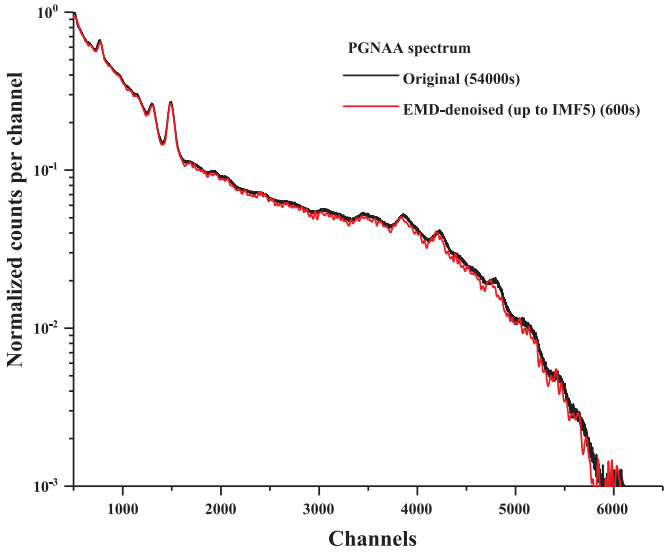

Fig. 6. Original and denoised PGNAA gamma ray spectra. The noise reduction performed with EMD technique where the summation of IMF1 to IMF5 has been subtracted from S(x) spectrum.

normally used in wavelet method and also the optional settings can be simply incorporated. The noise reduction of PGNAA spectrum has been undertaken with Daubechies (DB), biorthogonal (Bior) and Haar basic functions in different levels and then compared. Finally it has been found that DB3 at level 5 represents the best noise reduction results as seen in Fig. 3. The EMD technique uses sifting–to–IMFs procedure for spectrum (or signal) decomposition as follows:

(1) Separate interpolations have been performed among maxima and minima of normalized short–time spectrum, S(x), to obtain upper and lower envelopes and their average function ($m_1(x)$).
(2) The PGNAA spectrum has been subtracted to obtain $h_1(x)$,

$$h_1(x) = S(x) - m_1(x)$$

(3) Steps (1) and (2) are repeated for $h_1(x)$ to form the average of upper and lower envelopes ($m_{11}(x)$). The subtraction of $m_{11}(x)$ from $h_1(x)$ gives $h_{11}(x)$:

$$h_{11}(x) = h_1(x) - m_{11}(x)$$

(4) Then steps (1) and (2) are repeated for $h_{11}(x)$ for k times.

$$h_{1k}(x) = h_{1(k-1)}(x) - m_{1k}(x)$$

The process continues until the standard deviation falls between 0.2 and 0.3 (Huang et al., 1998) following Eq. (2).

$$SD = \sum_x \frac{|h_{new}(x) - h_{old}(x)|^2}{h_{old}^2(x)} \quad (2)$$

Hence $h_{1k}(x)$ is then called IMF_1 which is the first building component of spectrum with highest frequency compared to other components.

(5) Now, the IMF_1 component is subtracted from S(x) spectrum and the new spectrum, $r_1(x)$, has been obtained:

$$r_1(x) = S(x) - IMF_1$$

(6) Steps (1) to (4) on $r_1(x)$ are repeated to calculate $h_{2k}(x) = IMF_2$, the second component of spectrum and then $r_2(x)$ is calculated through $r_2(x) = r_1(x) - h_{2k}(x)$. The procedure continues as IMF behaves similar to the spectrum trend or $r_i(x) \approx 0$. The number of IMFs depend on S(x) spectrum.

Therefore, using EMD technique, a spectrum (or signal), simply without any precondition, is decomposed into a linear superposition of a number of IMF functions and a remainder which can be a constant value or a trend as follows:

$$S(x) = \sum_{i=1}^{n} IMF_i + r_n(x) \quad (3)$$

The above algorithm has been implemented using MATLAB in which the spline function due to its better performance has been utilized for interpolation among extrema. First, the capability of EMD technique has been examined by considering a combination of sinusoidal functions together with an additional noise. The results confirm the noise reduction capability of the proposed method.

The S(x) spectrum has been decomposed into 15 IMF components as shown in Fig. 4. To perform noise reduction, the spectrum subtractions from IMFs has been calculated following Eq. (4). The resulting spectra have been compared with reference spectrum, R(x), following Eq. (1), as shown in Fig. 5.

$$S_n(x) = S(x) - \sum_{i=1}^{n} IMF_i \quad (4)$$

2.3. Results and discussion

The sample spectra have been illustrated in Fig. 2. As seen, the spectrum is very noisy due to the large number of channels and short acquisition time (600 s). The reference spectrum exhibits low noise except in high–energy region (i.e., above 10 MeV). The pile up of pulses corresponding to chlorine and iron gamma rays with lower–energy ones is the main source of events dominated in above–10 MeV region of spectrum.

As seen in Fig. 3, the noise reduction undertaken using wavelet method with DB3 basic function at fifth level represents a good performance as gamma ray peaks are well distinguishable in denoised spectrum. The sum squared errors (MSE × L) value for the denoised short time spectrum compared to the normalized reference spectrum is 0.18.

In Fig. 4, the IMFs of normalized short–time spectrum, S(x), have been given. As it can be seen, the first few components demonstrate

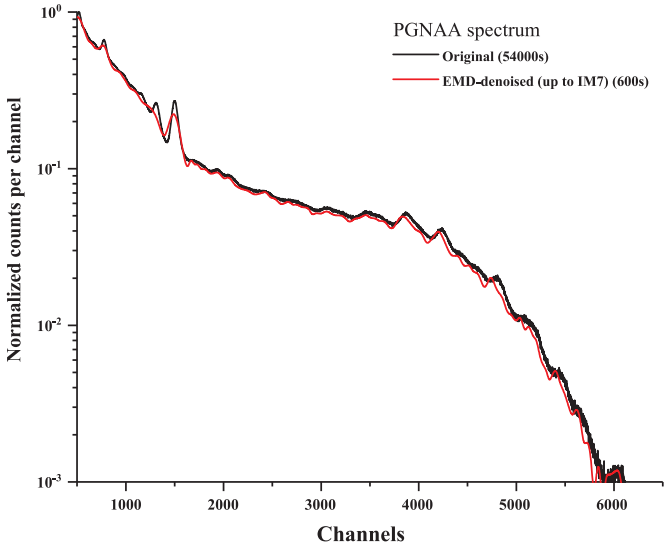

Fig. 7. Original and denoised PGNAA gamma ray spectra. The noise reduction performed with EMD technique where the summation of IMF1 to IMF7 has been subtracted from S(x) spectrum.

high frequencies which have to be omitted from the main spectrum. The subtraction of IMF1 to IMF5 components from S(x) spectrum, as seen in Fig. 5, leads to the best match with reference spectrum, S(x). This can be clearly seen by comparison between the spectra of Figs. 6 and 7.

3. Concluding remarks

The basic functions play important roles when implementing the wavelet method. Different basic functions have been studied and compared. Finally, it has been found that the DB3 function at level 5 represents the best noise–reduction performance on PGNAA spectrum. The EMD–denoised spectrum when the summation of IMF1 to IMF5 have been subtracted from the original spectrum, similar to wavelet method, results in a mean square error of 0.18, when compared to reference spectrum. Both EMD and wavelet methods exhibit promising results in the noise reduction of PGNAA gamma rays measured with NaI (Tl) scintillator in which the major peaks are well distinguishable as in reference spectrum. Overall, it can be concluded that the EMD technique is more preferable compared to wavelet method when dealing with PGNAA spectra. This is because the EMD technique uses that original spectrum data and it does not need any precondition. The simplicity and high computation speed are also two important factors of EMD technique.

Acknowledgements

Authors would like to thank the anonymous reviewers for careful reading of the manuscript and their helpful comments

References

Akkurt, H., 2002. Composition analysis of large samples with PGNAA using a fixed point iteration, Ph.D. dissertation. University of Michigan, U. S.
Barzilov, A., Kessler, B., Womble, P.C., 2015. Analysis of 14–MeV neutron induced gamma–ray spectra using multiwavelets. Radiat. Meas. 79, 43–49.
Bayat, E., Afarideh, H., Davani, F.A., Ghal–Eh, N., 2016. A quality survey on different shielding configurations of gamma ray detector used with a portable PGNAA system. Radiat. Phys. Chem. 120, 7–11.
Bergaoui, K., Reguigui, N., Gary, C.K., Brown, C., Cremer, J.T., Vainionpaa, J.H., Piestrup, M.A., 2014. Monte Carlo simulation of explosive detection system based on a Deuterium–Deuterium (D–D) neutron generator. Appl. Radiat. Isot. 94, 118–124.
Boudraa, A.O., Cexus, J.C., Saidi, Z., 2007. EMD–based signal noise reduction. World Acad. Sci. Eng. Technol. Int. J. Electr. Comput. Energy Electron. Commun. Eng. 1 (2), 313–316.
Charbucinski, J., Malos, J., Rojc, A., Smith, C., 2003. Prompt gamma neutron activation analysis method and instrumentation for copper grade estimation in large diameter blast holes. Appl. Radiat. Isot. 59 (2), 197–203.
Colominas, M.A., Schlotthauer, G., Torres, M.E., 2014. Improved complete ensemble EMD: a suitable tool for biomedical signal processing. Biomed. Signal Process. Control 14, 19–29.
Doostmohammadi, V., Sardari, D., Nasrabadi, A.M., 2010. Combined application of Monte Carlo method and neural networks to simulate qualitative prompt gamma neutron activation analysis. J. Radioanal. Nucl. Chem. 283 (2), 403–407.
Gardner, R.P., Xu, L., 2009. Status of the Monte Carlo library least–squares (MCLLS) approach for non–linear radiation analyzer problems. Radiat. Phys. Chem. 78 (10), 843–851.
Ghal–Eh, N., Ahmadi, P., Doost–Mohammadi, V., 2016. A quantitative PGNAA study for use in aqueous solution measurements using Am–Be neutron source and BGO scintillation detector. Nucl. Instrum. Methods Phys. Res. Sect. A: Accel. Spectrom. Detect. Assoc. Equip. 808, 123–127.
Gozani, T., Strellis, D., 2007. Advances in neutron based bulk explosive detection. Nucl. Instrum. Methods Phys. Res. Sect. B: Beam Interact. Mater. At. 261 (1), 311–315.
Huang, N.E., Shen, Z., Long, S.R., Wu, M.C., Shih, H.H., Zheng, Q., Yen, N.C., Tung, C.C. and Liu, H.H., 1998, March. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non–stationary time series analysis. In: Proceedings of the Royal Society of London A: Mathematical, Physical and Engineering Sciences (Vol. 454, No. 1971, pp. 903–995). The Royal Society.
Lim, C.S., Abernethy, D.A., 2005. On–line coal analysis using fast neutron–induced gamma–rays. Appl. Radiat. Isot. 63 (5), 697–704.
Martis, R.J., Acharya, U.R., Ray, A.K., Chakraborty, C., 2011. August. Application of higher order cumulants to ECG signals for the cardiac health diagnosis. In: Engineering in Medicine and Biology Society, EMBC, 2011 Annual International Conference of the IEEE, pp. 1697–1700.
Oden, C.P., Schweitzer, J.S., McDowell, G.M., 2006. The feasibility of well–logging measurements of arsenic levels using neutron–activation analysis. Appl. Radiat. Isot. 64 (9), 1074–1081.
Originlab2017. ⟨www.originlab.com⟩.
Rojas, A., Górriz, J.M., Ramírez, J., Illán, I.A., Martínez–Murcia, F.J., Ortiz, A., Río, M.G., Moreno–Caballero, M., 2013. Application of empirical mode decomposition (EMD) on DaTSCAN SPECT images to explore Parkinson disease. Expert Syst. Appl. 40 (7), 2756–2766.
Singh, B.N., Tiwari, A.K., 2006. Optimal selection of wavelet basis function applied to ECG signal denoising. Digit. Signal Process. 16 (3), 275–287.
Su, W.H., Lee, C.K., Lee, C.W., 2010. Noise–reduction for fringe analysis using the empirical mode decomposition with the generalized analysis model. Opt. Lasers Eng. 48 (2), 212–217.
Tarantola, A., 2005. Inverse Problem Theory and Methods for Model Parameter Estimation. Published by Society for Industrial and Applied Mathematics, SIAM, U. S.
Tsolis, G., Xenos, T.D., 2011. Signal denoising using empirical mode decomposition and higher order statistics. Int. J. Signal Process. Image Process. Pattern Recognit. 4 (2), 91–106.
Wang, T., Zhang, M., Yu, Q., Zhang, H., 2012. Comparing the applications of EMD and EEMD on time–frequency analysis of seismic signal. J. Appl. Geophys. 83, 29–34.
Yin, X., Xu, B., Jiang, C., Fu, Y., Wang, Z., Li, H., Shi, G., 2015. NIRS–based classification of clench force and speed motor imagery with the use of empirical mode decomposition for BCI. Med. Eng. Phys. 37 (3), 280–286.