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GENETIC ALGORITHMS TO DETERMINE THE OPTIMAL PARAMETERS OF AN ENSEMBLE LOCAL MEAN DECOMPOSITION

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Abstract. An optimization method for an ensemble local mean decomposition (ELMD) parameters selection was proposed by using evolutionary algorithms. ELMD is an adaptive, non-stationary and non-linear signal processing method based on the addition of different white noises to the target signal to be decomposed into a local mean decomposition (LMD) in order to solve its large mode mixing problem. Even though it has satisfactory performance for fault diagnosis of rotating machinery and reduced maintenance costs, the execution of this technique depends heavily on the correct choice of the parameters of its model. Although it was proposed to optimize the selection of these parameters through relative root-mean-square error (RRMSE) and signal-to-noise ratio (SNR), the optimized ensemble local mean decomposition (OELMD) based its selection by testing several values for amplitude, noise bandwidth and ensemble trials in order to obtain the optimum value. However, even with excellent signal processing results, this technique can raise computational costs and become prohibitive, especially in real-time analysis. Thus, this work also proposed an optimized ELMD, but in this occasion using the inclusion of genetic algorithms. The effectiveness of the proposed method was evaluated using synthetic signals, which was used by several authors for such purposes. Despite presenting inferior results to OELMD in avoiding mode mixing problem, the suggested algorithm obtained better results regarding the signal processing time.

Keywords: ensemble local mean decomposition; genetic algorithms; signal processing; optimization

1 Introduction

Due to the wide variety of application, several signal processing techniques have been developed in recent years [1]–[4]. In 1998, a great progress in so-called decomposition techniques occurred when

[1] introduced the empirical mode decomposition (EMD) which was an effective tool for non-linear and non-stationary signal analysis. In this method, a complex signal could be decomposed on a series of sum of finite functions that signify the oscillatory components of the signal and are called intrinsic mode functions (IMD). However, one the major disadvantages of this technique is its susceptibility to the mode mixing phenomenon. [4]. Mode mixing is defined where a unique *IMF* consists in signals with different modes. In this sense, in 2005, the local mean decomposition (*LMD*) [2] was developed in order to solve de mode mixing problem in applications in electrocardiograms and electroencephalograms.

Nevertheless, when tested against highly complex and contaminated signals, such as faulty mechanical components vibration, despite presenting superiority to EMD [5] the LMD still presents, in a prohibitive way, the mode mixing problem. Therefore, in order to improve its applicability in complex signals [3] proposed an ensemble local mean decomposition (EMD), which adds white noise to the vibration signals and thus, it is expected to obtain the optimal compositions of the signals. Meanwhile, in accord with [4] the effectiveness of ELMD in reducing mode mixing is highly influenced by its parameters, such as white noise amplitude, bandwidth and ensemble numbers. Although, few studies have been found to optimize the ELMD parameters in order to analyze its applicability in real vibration signals. [4] proposed an optimized ensemble local mean decomposition (OELMD), an optimization of ELMD, which its parameters are chosen to satisfy the decomposition performance. However, the technique used a gross-based method when testing several values for the parameters individually in order to find the optimum, leading to a highly prohibitive

In this scope of optimization, the genetic algorithms (GA) are techniques of search for the best result based on the principles of genetics and natural selection strongly studied [6–13] and disseminated since 1970s. A GA allows that a population composed of various individuals get involved in certain rules that minimize (or maximize) a cost function. This article proposes a new approach in the optimization of ELMD parameters to satisfactorily fulfill the decomposition performance. Thus, better results than the ELMD with regards to the mode mixing problem are expected, as well as better results than OELMD in terms of processing time. Although inspired in previously works [4], [14] in which were conceptualized using a method that used a variable relative root-mean-square error (RRMSE) and signal-to-noise ratio (SNR) to optimize the white noise parameters, none of these studies came to investigate the use of genetic algorithms to reduce the number of iterations necessary to search the parameters. Thus, this work brings as contributions: (a) development of a new procedure based on genetic algorithms to determination of white noise parameters in an ELMD; and, (b) continuation of the work of [4] on the investigation of RRMSE and SNR in optimal parameters selection.

2 Local mean decomposition

Assuming that a signal can be represented as the sum of a finite set of product function from which it is possible extract instantaneous frequency imbued with physical meaning, [2] has developed a method that consist basically in decompose the signal in several others functions, obtained from the product between an envelope signal and a frequency modulated signal, from which is possible extract the instantaneous frequency, thus can be represented as a time function and as a frequency function, giving rise to representations time-frequency (RTF).

In the method proposed by the author, the signal decomposition is performed by progressive decoupling of the frequency modulated signal from an amplitude modulated envelope, contemplating the following steps:

1) Obtaining all the local extremes from the signal $x(n)$. The extreme points are denoted by and the correspondent extremes by.

2) Calculation of smoothed local mean *m(t)* and smoothed local amplitude *a(t)*. To acquire these values are necessary two preliminary steps. The first one, characterized by the calculation of the preprocessed local mean and the local amplitude , it is obtained by:

$$\begin{cases} m^0(n) = \dfrac{x(e_k) + x(e_{k+1})}{2} para\, e_k \le n < e_{k+1} \\ a^0(n) = \dfrac{|x(e_k) - x(e_{k+1})|}{2} para\, e_k \le n < e_{k+1} \end{cases} \tag{1}$$

However, despite the simplicity and consistency of equations, Wang *et al.* [15] warn that results cannot be obtained without the signal being extended, which may introduce disagreements in the signal end that gradually influence its interior, disturbing the decomposition performance. Thus, the authors proposed a treatment for the extremes, which it is called boundaries processing method and calculates local mean and local amplitude, by means of giving equations.

$$\begin{cases} m^0(0) = \dfrac{x(e_1) + 2x(e_2) + x(e_3)}{4} \\ a^0(n) = \dfrac{|x(e_1) - x(e_2)| + |x(e_2) - x(e_3)|}{4} \end{cases} \tag{2}$$

$$\begin{cases} m^0(M) = \dfrac{x(e_{M-2}) + 2x(e_{M-1}) + x(e_M)}{4} \\ a^0(M) = \dfrac{|x(e_M) - x(e_{M-1})| + |x(e_{M-1}) - x(e_{M-2})|}{4} \end{cases} \tag{3}$$

Where M is the signal length. By other hand, Liu *et al.* [17] determined a signal extension algorithm, which modified the extremes by a spline interpolation, being this, an evolution for the works of Rilling *et al.* [18], which have applied in an EMD code.

Posteriorly, from the variables $m^0(n)$ and $a^0(n)$, the smoothed local mean *m(t)* and smoothed local amplitude *a(t)* are obtained. There are differences in how this smoothing is calculated. Although the method proposed by [2], using the moving average algorithm (MA) has been studied and with proven efficacy [3, 5, 16, 17, 19], Li *et al.* [20] argue that this methodology could lead the decomposition to incoherent results. Thus, [21] proposed a cubic spline interpolation based LMD (SLMD) due its property o good convergence and high smoothing. However, [22] affirm that for this method large interpolation errors can occur in the local amplitude calculation. Thereby, the authors have proposed a rational Hermite interpolation (OLMD), replacing spline interpolation, stating that it could better counteract the waveform of the amplitude. Nevertheless, [20] affirm that Hermite interpolation cannot adaptively adjust the shape curves with the varying local characteristics of the waveform in the sifting process. Therefore, the authors suggest that a rational spline Interpolation coupled with an optimization procedure of a tension parameter can control the shape of the cubic spline. According to the authors' studies, their method contributes with more accurate and exact results of decomposition as well as reduced the total processing time of the technique. Some smooth examples are show in Figure 1.

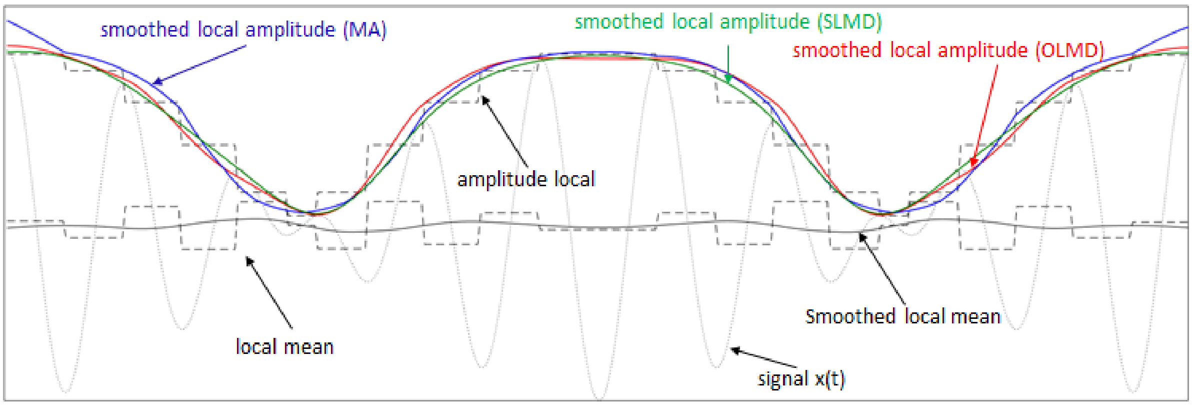

Figure 1. Hypothetical signal x(t) together with the local mean, smoothed local mean, local amplitude and local mean

3) Calculate the estimated zero-mean signal $h_{11}(n)$ and FM signal $s_{11}(n)$ by means of the variables *x(n)*, *m(n)* and *a(n)*. For that, the equation is defined by:

$$\begin{cases} h_{11}(n) = x(n) - m_{11}(n) \\ s_{11}(n) = \dfrac{h_{11}(n)}{a_{11}(n)} \end{cases} \tag{4}$$

It is important make sure that must be a purely FM signal. Otherwise, the function *x(n)* assumes the value of and the steps are repeated until the condition described by the equation is satisfied. This condition is so-called sifting process.

$$\lim_{p\to\infty} a_{1p}(n) = 1 \tag{5}$$

Due to its notorious importance in the LMD final results [20], Liu *et al.* [17] have proposed a method called sifting stopping, which defines an optimal number of iteration for the decomposition, which consequently brought better results for the method as well as reduced processing time.

4) Calculation of the signal $s_1(n)$, envelope signal $a_1(n)$ and the product function PF_1 after the execution of the sifting process. Considering the process with p iterations, the values of $s_1(n)$, $a_1(n)$ e $FP_1(n)$, and are given by:

$$\begin{cases} s_1(n) = s_{1p}(n) \\ a_1(n) = \prod_{j=1}^{p} a_{ij}(n) \\ FP_1(n) = a_1(n) \cdot s_1(n) \end{cases} \tag{6}$$

5) Subtract the product function from the signal *x(n)*. The process must be repeated *m* times until the entire signal is decomposed, so that:

$$x(n) = \sum_{i=1}^{m} FP_i(n) \tag{7}$$

2.1 Ensemble local mean decomposition

Components of the product function with different characteristics are obtained by means of the LMD method. However, due to signal discontinuity, mode mixing still occurs during the LMD process. This condition causes ambiguity in the physical meaning of the instantaneous frequencies of the product function after decomposition.

In view of this, Yang *et al.* [3] demonstrated that the addition of different Gaussian white noises to the signal prior to its decomposition by the LMD could drastically decrease the mode mixing phenomenon. Although it may seem that the addition of the disturbance to the signal could reduce the signal-to-noise ratio (SNR) and consequently bring erroneous results to the decomposition, due to the addition of a nonexistent product function, the authors proved that because they are several white Gaussian noises independent, the average of all added would tend to zero. Thus, the technique repeatedly applies the LMD method to the signal along with a Gaussian white noise of finite amplitude. The average of the product functions derived from the various applications is used as the result of the decomposition. Since the mean noise is zero, all disturbance added can be considered as excluded. This technique was known as the ensemble local mean decomposition (ELMD) and added far superior to LMD in problems in fault diagnosis in rotating machines [3, 19, 23].

According to Sun *et al.* [24] ELMD can be described by the following steps:

1) Adding white noise to the signal *x(t)* thus forming *y(t)*.
2) Application of the LMD in signal *y(t)* in order to obtain multiple product functions.
3) Repeat steps 1 and 2 several times and with different noises added in each iteration.
4) Calculation of the mean of the PF obtained and consequent use of this as the result of the decomposition.

3 Ensemble local mean decomposition based on genetic algorithms

The operation of a genetic algorithm is based on the principles of genetics and natural selection. An GA allows a population composed of many individuals to be involved in some natural selection rule so that the final population is the one that fit the most.

Thus, the first step in GA determination is the definition of the environmental condition for the population, in this case, the cost function. For this work, in defining the optimal parameters for the white noise to be added to the signal, it is essential that it present a maximum RRMSE value, which evaluates the difference between the product functions and the original signal in order to cancel the mode mixing, and the SNR, which determines whether the effects of insertion of the noise into the signal have been negated. Therefore, it is possible to establish the conforming cost function.

$$Cost = -RRMSE \cdot SNR \tag{8}$$

Thence, the definition of an initial population, which can be formed by totally random chromosomes or by initial guesses in order to improve the convergence of the algorithm. In the proposed methods, populations are defined in two different ways. For the first case, GA1, the population is defined totally randomly.

$$Population = rand(N_{cro}, N_{var}) \tag{9}$$

Where, N_{cro} represents the number of chromosomes of a population and N_{var} represents the number of alleles contained in the chromosome. For this work, the number of alleles is equal to three, representing the white noise amplitude, bandwidth frequency and number of ensembles. In the second case, for the methods proposed in GA2 and GA3, the first allele is given by Eq. 10, while the remnants are still randomly chosen. The values chosen for population formation were based on previous studies [4], which demonstrate that the optimum amplitude range normally between 20 and 50% of the maximum amplitude of the studied signal.

$$Population = \max[x(t)] \cdot [0.2; 0.3; 0.4; 0.5] \tag{10}$$

In sequence, the pairing is defined, where the most adapted chromosomes are put in a way to cross. Parents and mothers are randomly defined, and each pair produces two descendants that contain traits of each parent. Parents still survive to be part of the next generation. The more similar the two parents are, the more likely the convergence for a final population.

Once the pairing has been defined, the crossing step is taken. For this, several methodologies were developed to optimize the creation of descendants. The simplest crossing methods are so-called point crossing [9]. In these, one or more points of the chromosomes are selected as crossing points. Then the variables between these points are exchanged between the two parents. However, the great disadvantage of this technique is that there is no new information in the generation of the individuals, which are only a replica of the random values provided by the initial population. Thus, a variation of this method was suggested, the so-called simple crossing [10]. In this methodology, a descendant comes from the combination of parents, but so that the chromosome assumes new values, even if still related to the predecessors. The formation of an allele for this chromosome is demonstrated by.

$$allele_{new} = \propto \cdot\, allele_{mom,n} + (1-\propto) \cdot allele_{dad,n} \qquad (11)$$

Being $\propto$: random number between 0 and 1; $allele_{mom,n}$: nth allele on the mother chromosome, e; $allele_{dad,n}$: nth allele on the father chromosome. It is noted that at the simple crossing, if the value of $\propto = 0.5$, the allele of the descending chromosome becomes a simple mean of the parental variables. However, although this method allows the entry of new information combining information from the parents, it does not allow the inclusion of values outside the extreme values of the parents. Thus, another approach proposed by [10] was the heuristic cross which again uses a random variable, β, to define one or more descendant alleles.

In this work, the use of the heuristic crossing in the implementation of the algorithm was defined as it presented better results in the search for the global maximum [11]. In this way, always in the generation of a new population lineage, for at least one allele of each descendant is imposed this crossing. This is chosen randomly and the remaining variable is fairly distributed to the children, so that each parent is always represented.

$$allele_{new} = \beta \cdot (allele_{mom,n} - allele_{dad,n}) + allele_{mom,n} \qquad (12)$$

Finally, some form of mutation can be defined for some chromosomes of the population. The mutation process is important in some cases where a function may have several local maxima and the cost function converges to one of these minima. If there is no precautionary measure, the result may be far from the overall maximum cost. In this work, the mutation process is defined in one of the proposed methods, GA3. In this, the mutation is defined totally randomly, where a random value between 0 and 1 is calculated. If this is greater than 0.8 (arbitrarily chosen) a chromosome is recalculated at random, without any correlation with its parents. The proposed method is exemplified by the flowchart shown in Figure 2, which is an application of genetic algorithms in the method proposed by [3].

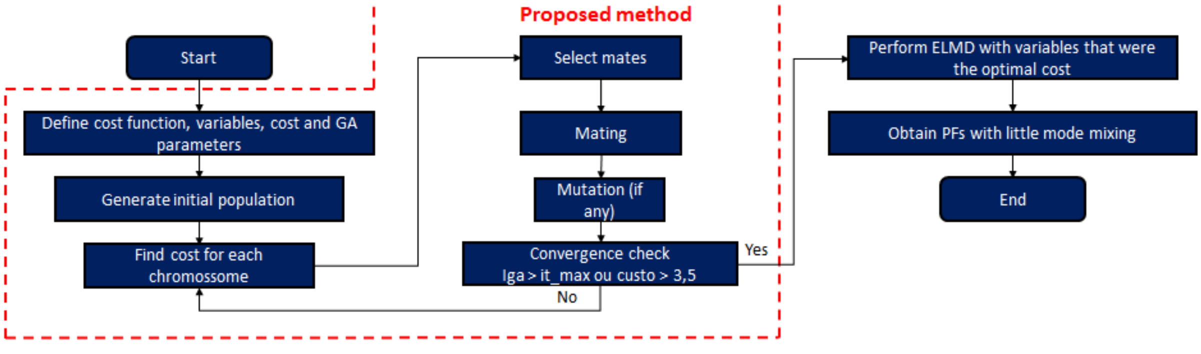

Figure 2. Flowchart of the method defined in the genetic algorithms for parameter selection.

4 Simulated single test

For the evaluation and application of the proposed technique of parameter selection, a synthetic signal $x(t)$ is defined (Figure **3**) which was proposed by [4] and consists of three components in Equation 19, 20 and 21. This specific signal was chosen for no other reason than to compare the effectiveness of the proposed method to a widespread recognized research which presents a similar approach towards an ensemble local mean decomposition. Therefore, several other signals could be used in order to reach the same result with no prejudice to the general understanding of the idea presented. Since it is often impossible to know all the compositions of a real signal, the use of synthetic signals is very important for the evaluation of a signal processing methodology.

$$\begin{cases} x(t) = x_1(t) + x_2(t) + x_3(t) \\ x_1(t) = 1{,}5 \cdot e^{-800t'} \cdot sen(2\pi \cdot 5000t) \\ x_2(t) = 0{,}2 \cdot (1 + cos(2\pi \cdot 100t) \cdot \cos(2\pi \cdot 1000t)) \end{cases} \tag{13}$$

And, $x3(t)$ is white Gaussian noise with bandwidth from 2 to 4 kHz, and; t' is a periodic function with fundamental period of 1/160s. According to the author, this frequency was chosen because, when compared with low frequency noises, high frequencies generally present larger contributions to the change in the extremes of the original signal.

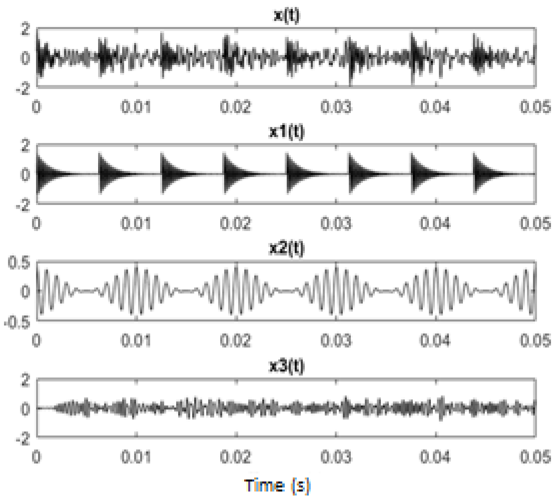

Figure 3. Waveform in the time domain of the signal x(t), x1(t), x2(t) and x3(t).

In order to compare the performance of the proposed GAB-ELMD and OELMD and LMD methods (using the smoothing method the moving average and the optimization in the proposed sifting process) root-mean-square error (RMSE), number of product functions and processing time are considered as the three indicators. The expression for the RMSE is given by:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}[x_i(t) - PF_i(t)]^2}{N}} \tag{14}$$

Where $x_i(t)$ and $PF_i(t)$ are the original components of the signal and its corresponding decomposed by the method, respectively. A lower RMSE value indicates better execution performance. The computer used for the simulation is a 2.4 GHz i7-Dual Core processor and 8 GB RAM. The software used is MATLAB (R2018b). The tests were run ten times and the results shown in Table 1 represent the means of the results obtained.

The proposed methods, based on genetic algorithms, had presented results similar to OELMD technique in relation to decomposition performance. In terms of computational cost, OELMD used a much longer time due to its characteristic of test and analysis, while all the techniques proposed obtained much shorter times without major losses in the quality of the processed signal. However, still searching for better values, we propose another algorithm, GAB, in which some changes are made, as in the cost function, which will be described as follows.

$$Cost = -RRMSE \tag{15}$$

Thus, the selection is based on genetic algorithms only for the selection of the amplitude variable of the noise. As for the number of compositions, in the GAB, it is selected in a similar way to that proposed by [4] in the OELMD, but with the execution of the test without the realization of the decompositions by the LMD. This is because, according to the author, the number of compositions is inserted as a property to precisely define that the white noise added by the ELMD did not imply any influence on the original signal. Therefore, it is expected that there is no need to perform the decomposition, a fact that consumes a lot of time in the verification of the signal-to-noise ratio.

Thus, the simulation performed for the GAB algorithm obtained 0.1743; 0.1183 and 0.1914 of root-mean-square error for components 1, 2 and 3 respectively. The results were obtained in 18.6 seconds, indicating a 94% drop in the time of choice of the parameters for the original OELMD algorithm.

5 Proposed algorithm for improvement in decomposition results

After the signal is decomposed by GAB-ELMD, some product functions still present the mode mixing phenomenon, which could be observed in the previous section. Although it is an intrinsic phenomenon of the ELMD method, since the mix had also been high values, mainly in PF3, both in OELMD and GAB-ELMD, it is proposed in this work the reapplication of the decomposition based on RRMSE in order to reduction of the mode mixing problem. Recent works like [14] and [4] have already investigated the use of RRMSE as a measure parameter of the mix of modes between product functions, but none of them used this parameter in order to reapply the decomposition in the functions products that presented the highest RRMSE. Based on the characteristics of this function, reapplication of decomposition is based on the following steps.

1) GAB-ELMD is initially applied to decompose the signal.
2) The RRMSE matrix is then calculated. In this, it is possible to compare the relative root-mean-square-error between the product functions. In this way, it is expected to find the product function that presented the greatest mix of modes (minimum value).

Table 1. Performance comparison between OELMD and proposed methods

Métodos	RMSE			Number of PFs	Tempo (s)
	PF1	PF2	PF3		
OELMD	0,171 ± 0,017	0,125 ± 0,006	0,198 ± 0,013	3	310.5
GAB1	0,174 ± 0,022	0,128 ± 0,007	0,202 ± 0,014	3	140.8
GAB2	0,163 ± 0,038	0,117 ± 0,038	0,190 ± 0,041	3	131.2
GAB3	0,161 ± 0,035	0,115 ± 0,034	0,187 ± 0,037	3	132.6

$$M = \begin{bmatrix} RMSE(PF_i, PF_i) & \cdots & RMSE(PF_i, PF_j) \\ \vdots & \ddots & \vdots \\ RMSE(PF_j, PF_i & \cdots & RMSE(PF_j, PF_j \end{bmatrix} \tag{17}$$

3) The PF that presents the biggest problem of mode mixing is selected.
4) LMD is applied to the PF previously selected.

Table 2. Comparison of performance between proposed algorithm and methods discussed in Section 2.

Methods	RMSE			Number of PFs
	PF1	PF2	PF3	
SLMD	0,3305	0,1343	0,3014	3
OLMD	0,3305	0,1335	0,3017	3
ILMD	0,2107	0,0862	0,3016	4
OELMD	0,1896	0,1242	0,2002	3
Proposto	0,1202	0,0753	0,1360	3

5) Each new product function is compared through the RRMSE with the PFs obtained in step 1. The PF of step 1 that obtains the closest resemblance to the new one will be added to it or replaced by that one (if the PF is selected in the third step).
6) The procedure is repeated from step 2 to 5 until the lowest value in the RRMSE array is greater than or equal to 1, or the number of desired maximum iterations is reached.
7) Gets the product functions with the least mix of modes.

In order to compare the effectiveness of the proposed method we used the hypothetical signal defined by Equation 13, which was decomposed by the methods mentioned in Section 2 as shown in Figure 3, which displays the product functions in both time domain and frequency domain. Thus, the PFs obtained (Figures4-8) by them were again compared to the respective components of the original signal by means of the RMSE variable and the values are then presented in Table 2.

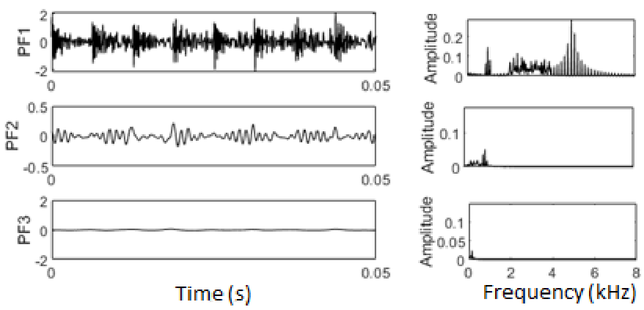

Figure 4. Signal in time domain (left) and frequency domain (right) by SLMD method.

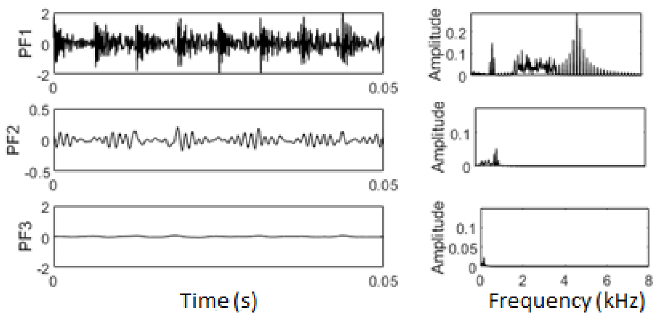

Figure 5. Signal in time domain (left) and frequency domain (right) by OLMD method.

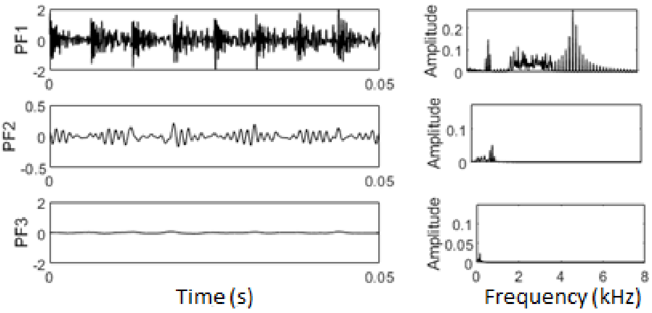

Figure 6. Signal in time domain (left) and frequency domain (right) by ILMD method.

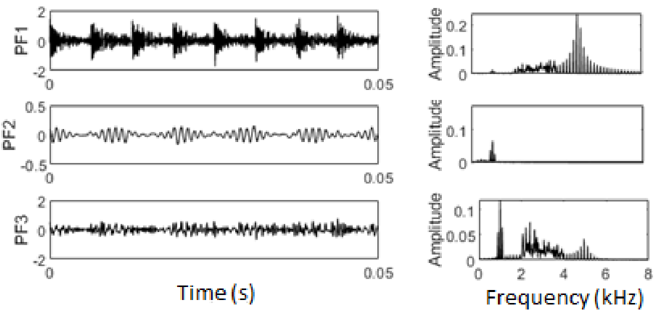

Figure 7. Signal in time domain (left) and frequency domain (right) by OELMD method.

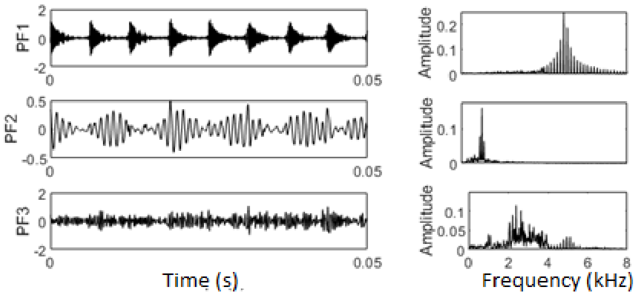

Figure 8. Signal in time domain (left) and frequency domain (right) by proposed method.

6 Conclusion

The objective of this work was to apply a well-known genetic based optimization technique to a signal processing methodology in order to improve its results. The major drawback in ELMD is its dependence on the appropriate choice of the white noise parameters to be added in the signal. In the literature, only was found methodology based on brute-force tests for this purpose, however, in this, the processing time becomes an inconvenience.

In the programming of the algorithms, three different cases were initially proposed, varying in some known parameters of the genetic algorithms, such as the initial population and the insertion (or not) of some form of mutation. Although all the methods showed similarity in the results of the OELMD decomposition, all presented much better results in terms of processing time, reducing the total time by more than 50%. Also, it had been identified that one of the parameters could be determined in a simpler way, without executing the ELMD to identify its results. Thus, another algorithm, again based on genetic algorithms, was proposed, which reduced the total processing time by more than 90% when compared to OELMD, obtaining slightly higher results.

The decomposition reapplication based on the RRMSE values was also evaluated in order to mitigate the mode mixing problem, which was highly successful in its application to synthetic hybrid signals, presenting excellent results as shown in Table 2 and Figure 8.

Thus, even with some considerations in the execution of the algorithms, the results obtained in this work suggest a great applicability of genetic algorithms to obtain the optimal white noise parameters to be added to the signal in the ELMD. It is suggested as future work the application of the techniques - both the decomposition based on genetic algorithms and the reapplication of decomposition - into real signals. It is also suggested to use other optimization techniques, such as neural networks, for example.

Acknowledgements

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References

[1] N. E. Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Royal Society of London Proceedings Series A*, vol. 454, no. 1, pp. 903–995, 1996.
[2] J. S. Smith, "The local mean decomposition and its application to EEG perception data," *Journal of The Royal Society Interface*, vol. 2, no. 5, pp. 443–454, Dec. 2005.
[3] Y. Yang, J. Cheng, and K. Zhang, "An ensemble local means decomposition method and its application to local rub-impact fault diagnosis of the rotor systems," *Measurement*, vol. 45, no. 3, pp. 561–570, 2012.
[4] C. Zhang, Z. Li, C. Hu, S. Chen, J. Wang, and X. Zhang, "An optimized ensemble local mean decomposition method for fault detection of mechanical components," *Measurement Science and Technology*, vol. 28, no. 3, p. 035102, Mar. 2017.
[5] Y. Wang, Z. He, and Y. Zi, "A Comparative Study on the Local Mean Decomposition and Empirical Mode Decomposition and Their Applications to Rotating Machinery Health Diagnosis," *Journal of Vibration and Acoustics*, vol. 132, no. 2, p. 021010, 2010.
[6] I. Bruant, L. Gallimard, and S. Nikoukar, "Optimal piezoelectric actuator and sensor location for active vibration control, using genetic algorithm," *Journal of Sound and Vibration*, vol. 329, no. 10, pp. 1615–1635, May 2010.
[7] L. B. Jack and A. K. Nandi, "Genetic algorithms for feature selection in machine condition monitoring with vibration signals," *IEE Proc-Vis. Image Signal Process*, vol. 147, no. 3, pp. 205–212, 2000.
[8] H. Hao and Y. Xia, "Vibration-based Damage Detection of Structures," *Journal of Computing in Civil Engineering*, vol. 16, no. 3, pp. 222–229, 2002.
[9] A. A. Adewuya, "New Methods in Genetic Search with Real-Valued Chromosomes," Massachusetts Institute of Technology, 1996.
[10] Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*. Berlin, Heidelberg: Springer Berlin Heidelberg, 1996.
[11] R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, 2nd ed. Hoboken, NJ, USA: John Wiley & Sons, Inc., 2003.
[12] J. H. Holland, "Genetic Algorithms and the Optimal Allocation of Trials," *SIAM Journal on Computing*, vol. 2, no. 2, pp. 88–105, Jun. 1973.
[13] J. H. Holland, *Adaptation in Natural and Artificial Systems: An Introductory Analysis with Applications to Biology, Control and Artificial Intelligence*. Cambridge, MA, 1992.
[14] W. Guo and P. W. Tse, "A novel signal compression method based on optimal ensemble empirical mode decomposition for bearing vibration signals," *Journal of Sound and Vibration*, vol. 332, no. 2, pp. 423–441, 2013.

[15] Y. Wang, Z. He, and Y. Zi, "A demodulation method based on improved local mean decomposition and its application in rub-impact fault diagnosis," *Measurement Science and Technology*, vol. 20, no. 2, 2009.
[16] F. D. D. M. Borges, "Comparação de métodos de tratamento de sinais aplicáveis ao diagnóstico de defeitos em mancais de rolamento," Universidade Estadual do Oeste do Paraná, 2018.
[17] Z. Liu, M. J. Zuo, Y. Jin, D. Pan, and Y. Qin, "Improved local mean decomposition for modulation information mining and its application to machinery fault diagnosis," *Journal of Sound and Vibration*, vol. 397, pp. 266–281, Jun. 2017.
[18] G. Rilling, P. Flandrin, and P. Gonçalvès, "On empirical mode decomposition and its algorithms," in *6th IEEE-EURASIP Workshop on Nonlinear Signal and Image Processing*, 2003.
[19] L. Wang, Z. Liu, Q. Miao, and X. Zhang, "Complete ensemble local mean decomposition with adaptive noise and its application to fault diagnosis for rolling bearings," *Mechanical Systems and Signal Processing*, vol. 106, pp. 24–39, 2018.
[20] Y. Li, X. Liang, Y. Yang, M. Xu, and W. Huang, "Early Fault Diagnosis of Rotating Machinery by Combining Differential Rational Spline-Based LMD and K-L Divergence," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 11, pp. 3077–3090, 2017.
[21] L. Deng and R. Zhao, "An improved spline-local mean decomposition and its application to vibration analysis of rotating machinery with rub-impact fault," *Journal of Vibroengineering*, vol. 16, no. 1, pp. 414–433, 2014.
[22] Y. Li, M. Xu, Z. Haiyang, Y. Wei, and W. Huang, "A new rotating machinery fault diagnosis method based on improved local mean decomposition," *Digital Signal Processing*, vol. 46, pp. 201–214, 2015.
[23] L. Wang, Z. Liu, Q. Miao, and X. Zhang, "Time–frequency analysis based on ensemble local mean decomposition and fast kurtogram for rotating machinery fault diagnosis," *Mechanical Systems and Signal Processing*, vol. 103, pp. 60–75, Mar. 2018.
[24] J. Sun, Q. Xiao, J. Wen, and Y. Zhang, "Natural gas leak location with K-L divergence-based adaptive selection of Ensemble Local Mean Decomposition components and high-order ambiguity function," *Journal of Sound and Vibration*, vol. 347, pp. 232–245, 2015.