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Application of the EEMD and CEEMDAN algorithm for non-linear signal processing

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ABSTRACT

Nonlinear signals are often encountered in many applications, such as biomedical signal processing, fault diagnosis, and image processing. Ensemble empirical mode decomposition (EEMD) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) algorithms have been proposed for the analysis of nonlinear and non-stationary signals. In this paper, we compare the performance of EEMD and CEEMDAN algorithms based on the Root Mean Square (RMS) statistical indicator for nonlinear signal processing. We evaluate the effectiveness of these algorithms using two synthetic signals and a real-world vibration signal from a gearbox. The results show that CEEMDAN provides a 50% improvement over EEMD in terms of RMS and the number of trials or computation time required. The study also shows that EEMD is prone to mode mixing and requires a large number of trials to achieve accurate results. On the other hand, CEEMDAN overcomes the mode mixing issue and provides more accurate results with fewer trials or computation time. Our findings suggest that CEEMDAN is a more efficient algorithm for nonlinear signal processing, particularly in real-world applications where computation time is a limiting factor.

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1. INTRODUCTION

Nonlinear signal processing has gained increasing attention in various applications, such as biomedical signal analysis, fault diagnosis, and image processing [1]. Nonlinear signals are characterized by their complex and non-stationary nature, making their analysis and interpretation a challenging task[2]. Traditional signal processing techniques such as Fourier analysis and wavelet transform are inadequate for nonlinear signals due to their linear and stationary assumptions [3].

To address the limitations of traditional signal processing techniques, researchers have developed a range of non-linear signal processing methods, including the empirical mode decomposition (EMD) algorithm[2, 4]. EMD is a powerful technique for decomposing a non-linear and non-stationary signal into a set of intrinsic mode functions (IMFs) that capture the underlying oscillatory modes of the signal. However, EMD suffers from the mode mixing problem, which can affect the accuracy and reliability of the results[5, 6].

To overcome the limitations of EMD, the ensemble empirical mode decomposition (EEMD) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) algorithms have been proposed. EEMD generates multiple noise-added versions of the input signal and applies EMD to each version to obtain a set of IMFs[7]. CEEMDAN further improves upon EEMD by adapting the added noise based on the local characteristics of the signal[8, 9, 10]. These algorithms have shown promising results in the analysis of nonlinear and non-stationary signals, particularly in cases where traditional signal processing techniques fail to provide satisfactory results.

In this paper, we focus on the application of EEMD and CEEMDAN algorithms for nonlinear signal processing and compare their performance based on the Root Mean Square (RMS) statistical indicator. We evaluate the effectiveness of these algorithms using two synthetic signals and a real-world vibration signal from a gearbox. The results demonstrate the potential of these algorithms for nonlinear signal processing and highlight the importance of efficient algorithms for real-world applications.

The main difference between EEMD (Ensemble Empirical Mode Decomposition) and CEEMDAN (Complementary Ensemble Empirical Mode Decomposition with Adaptive Noise) lies in the way they handle the issue of mode mixing [11].

Mode mixing is a problem that can occur in empirical mode decomposition (EMD), which is the basis for both EEMD and CEEMDAN. Mode mixing occurs when two or more intrinsic mode functions (IMFs) with different physical meanings are mixed together in a single IMF, making it difficult to extract meaningful information from the decomposed signal.

EEMD attempts to solve the mode mixing problem by adding white noise to the original signal to generate multiple perturbed signals, and then applying EMD to each perturbed signal separately [12, 13]. The IMFs obtained from each perturbed signal are then averaged to reduce the effects of noise and non-stationarity, and to obtain the final IMF. However, the EEMD method still suffers from mode mixing to some degree[5, 13].

CEEMDAN improves on EEMD by introducing the concept of complementary ensemble. In addition to adding white noise to the original signal, CEEMDAN adds an ensemble of signals obtained by subtracting a low-pass filtered version of the original signal from the original signal. The IMFs obtained from both ensembles are then combined in a complementary way to obtain the final IMF[11, 14]. By combining the two ensembles in a complementary way, CEEMDAN is able to reduce mode mixing to a greater degree than EEMD.

In summary, while EEMD and CEEMDAN are both based on the EMD method and attempt to address the mode mixing problem, CEEMDAN uses a complementary ensemble approach that is more effective in reducing mode mixing and producing more accurate decompositions of non-linear and non-stationary signals [15, 16, 1].

2. METHODOLOGY THE PROPOSED METHOD

2.1. EEMD

Huang et al [17] first proposed EMD in 1999. It is a signal processing method, which can be used to process non-linear and non-stationary signals. However, EMD has some shortcomings, which can lead to the problem of "mode mixing"[18, 19]. In order to solve this problem, Wu and Huang [20] proposed the EMD-based EMD package in 2009. The steps of EMD are as follows [21]:

Step 1: Determine the standard Gaussian white noise g i (t) ~ N (0, σ 2), (the standard deviation σ is usually set to 0.1 or 0.2), the set number E and a loop variable i = 1.
Step 2: Add a white Gaussian noise gi (t) to the raw series Y (t) to obtain the following new series:

$$Y_i(t) = Y(t) + g_i \tag{1}$$

Step 3: Conduct EMD on Y_i (t) to obtain m intrinsic mode functions (IMF) and a residual series r_i (t) :

$$Y_i(t) = \sum_{j=1}^{m} C_{ij}(t) + r_i(t) \tag{2}$$

The term C_ij(t) represents the j-th IMF of the i-th perturbed signal, and r_i(t) represents the remainder of the i-th perturbed signal after all the IMFs have been extracted. The remainder captures the low-frequency behavior of the signal that cannot be represented by the IMFs.
where m = ⌊log 2 T⌋ - 1 [22], determined by the length of the raw series T.

Step 4: Add 1 to the loop variable i. If i > m, perform step 5; otherwise, return to step 2.

Step 5: Calculate the j th final MFI $C_{ij}(t)$ in E trials as shown in equation (5) :

$$C_{(t)} = \frac{1}{E}\sum_{j=1}^{i} C_{ij}(t) \tag{3}$$

Step 6: Obtain the residual series as shown in equation (6):

Finally, the raw series can be divided into m IMFs and a residual.

However, due to the difference in the chosen white noise, the mode functions obtained by decomposition are different, which makes EEMD unstable. And the EEMD method is difficult to completely eliminate the reconstruction error caused by the white Gaussian noise. In order to further solve these problems, Torres et al [22] [23] proposed CEEMDAN, based on EEMD in 2011, which can better obtain the intrinsic mode functions and accurately reconstruct the original signal, with a lower running cost than the EEMD algorithm.

2.2. Algorithm of the CEEMDAN method

In the EEMD method, each noisy realisation x(t) of the signal to be decomposed is decomposed independently of the other realisations and thus for each realisation x(t) a residual is obtained [24]:

$$r_k^i(t) = r_{k-1}^i(t) - IMF_k^i(t) \tag{4}$$

In the CEEMDAN method [11], the decomposition modes will be denoted $\overline{\overline{IMF}}$ (t) and a first residue is calculated:

$$r_1(t) = x(t) - \overline{\overline{IMF}}_1(\mathrm{t}) \tag{5}$$

$\overline{\overline{IMF}}_1$ (t) is obtained in the same way as in the EMD. Thus, the first EMD mode was calculated over a number of trials of $r1$ (t) and the different realisations of a white Gaussian noise giving access to $IMF2$ by averaging. The next residual is defined as:

$$r_2\,(t) = r_1(t) - \overline{\overline{IMF}}_2(t) \tag{6}$$

This procedure continues with the rest of the modes until the stopping criterion is reached. We define the operator $E_j\{.\}$ which produces the j^{ieme} mode obtained by the EMD decomposition. b_i(t) the white Gaussian noise and x(t) the target signal. The CEEMDAN method is described by the following algorithm [25, 26]:

1. Decompose by the EMD method the N_e realisations x(t) +Ɛb_i(t) ≤ i ≤ N_e to obtain their first mode which is the first mode of the CEEMDAN method $IMF_1\ (t)_{\mathrm{CEEMDAN}}$ noted IMF_1(t).

$$\overline{\overline{IMF}}_1(t) = \frac{1}{N_e}\sum_{i=1}^{N_e} IMF_1^i\,(t) \tag{7}$$

2. Calculate the first residue of the first phase (k =1):

$$r_1(t) = x(t) - \overline{\overline{IMF}}_1(t) \tag{8}$$

3. Decompose by the EMD method the N_e new achievements:
   $r_1(t) + \varepsilon E\{b_i(t)\} 1 \le i \le N_e$ To get their first mode which is the second mode:

$$\overline{\overline{IMF}}_2(t) = \frac{1}{N_e}\sum_{i=1}^{N_e} E_1\left\{r_1(t) + \varepsilon E_1\{b_1(t)\}\right\} \tag{9}$$

The residual of the second step (k=2) is:

$$r_2(t) = r_1(t)\overline{\overline{IMF}}_2(t) \tag{10}$$

4. Calculate the residual of the k^th phase:

$$r_2(t) = r_{k-1}(t)\overline{\overline{IMF}}_k(t) \tag{11}$$

5. Decompose the resulting achievements: $r_1(t) + \varepsilon E_k\{b_i(t)\}$, $\mathrm{i} = 1, \Lambda, N_e$, to the first EMD mode and sets the (k+1)^th mode :

$$\overline{\overline{IMF}}_{k+1}(t) = \frac{1}{N_e}\sum_{i=1}^{N_e} E_1\left\{r_k(t) + \varepsilon E_1\{b_1(t)\}\right\} \tag{12}$$

6. Go to step 4 of the algorithm for the next k.

Steps 4 to 6 are performed until the resulting residue is no longer decomposable (the residue does not have at least two extremums). The final residue is given by:

$$R(t) = x(t)\sum_{k=1}^{K} \overline{\overline{IMF}}_k \tag{13}$$

K est le nombre total de modes. Ainsi, le signal x(t) peut être exprimé comme suit :

$$x(t) = \sum_{k=1}^{K} \overline{\overline{IMF}}_k + R(t) \tag{14}$$

3. RESULTS AND DISCUSSIONS

3.1. Data Acquisition system

The vibration signals generated during machining were measured using an acquisition and analysis system, consisting of software and a piezoelectric accelerometer (X, Y, Z) compressed by a moving mass subjected to the vibrations to which the sensor is subjected. For a good acquisition, the PCB 080A27 type sensor was placed as close as possible to the machining area and on a fixed location as shown in figure 1

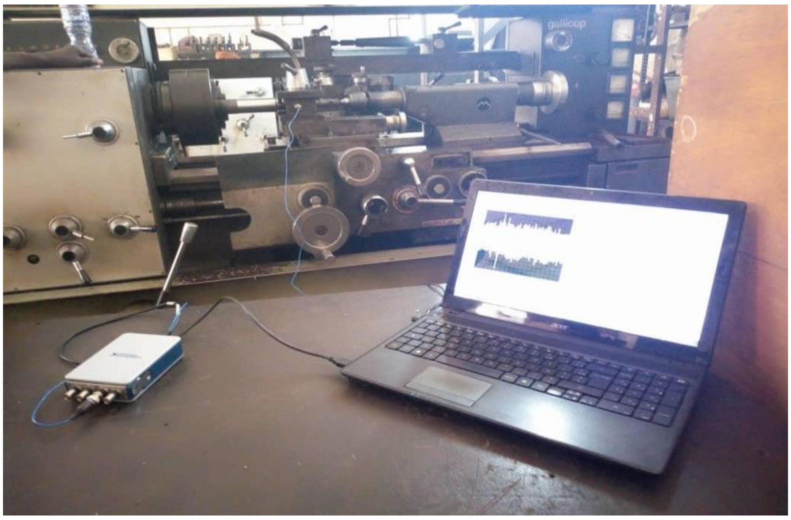

Figure 1. Data Acquisition system.

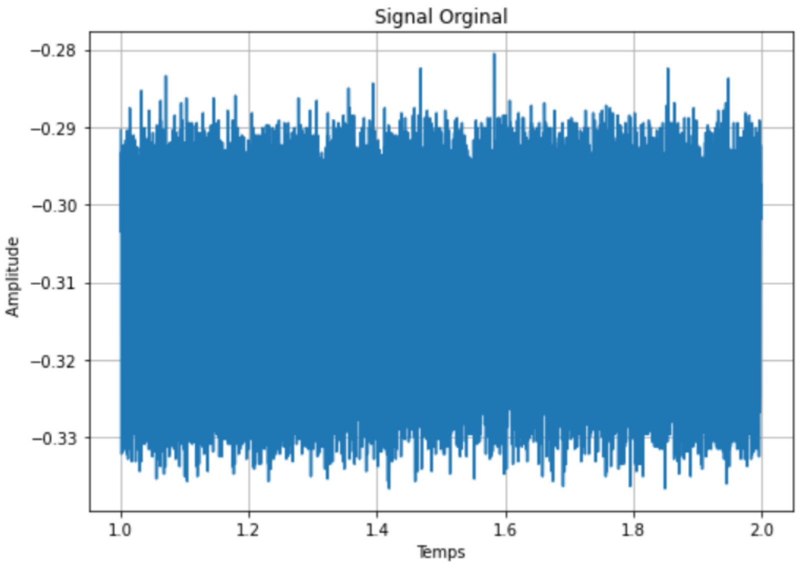

Figure 2. Vibration signal recorded

3.2. Application EEMD

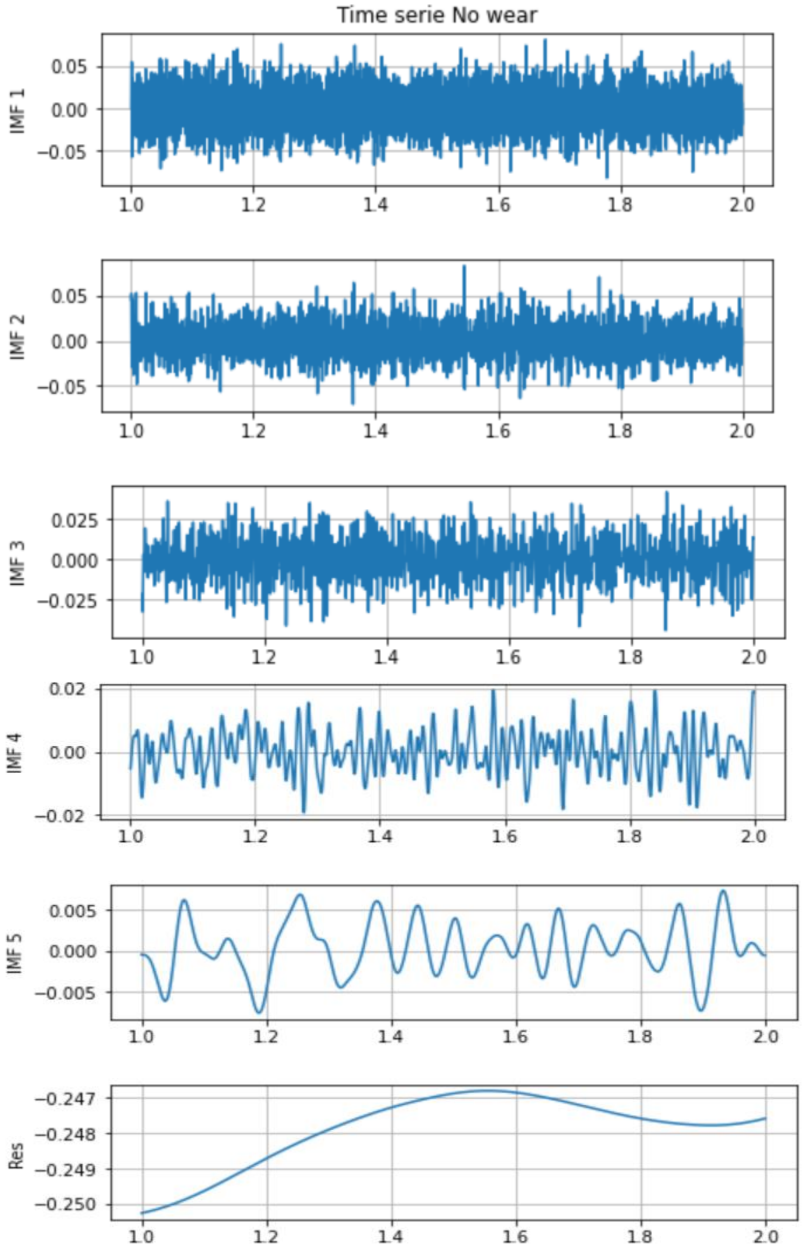

Figure 3. Decomposition of the signal into IMFs with the EEMD method

In the EEMD figure shown above, we have decomposed an original signal into IMFs. We have marked this:

- The decomposition is from high to low frequencies.
- As far as the decomposition of the IMFs in the EEMD method is concerned, we find IMF 5, from IMF1 to IMF2 are high frequency signals which are not useful. The low frequency signals start from IMF3 to IMF5 which are information carriers. Of these three low frequency IMFs we used IMF3 as our information carrier signal.
- The residual is non-zero which reflects an estimation error between the signal and the components.

3.1. CEEMDAN APPLICATION

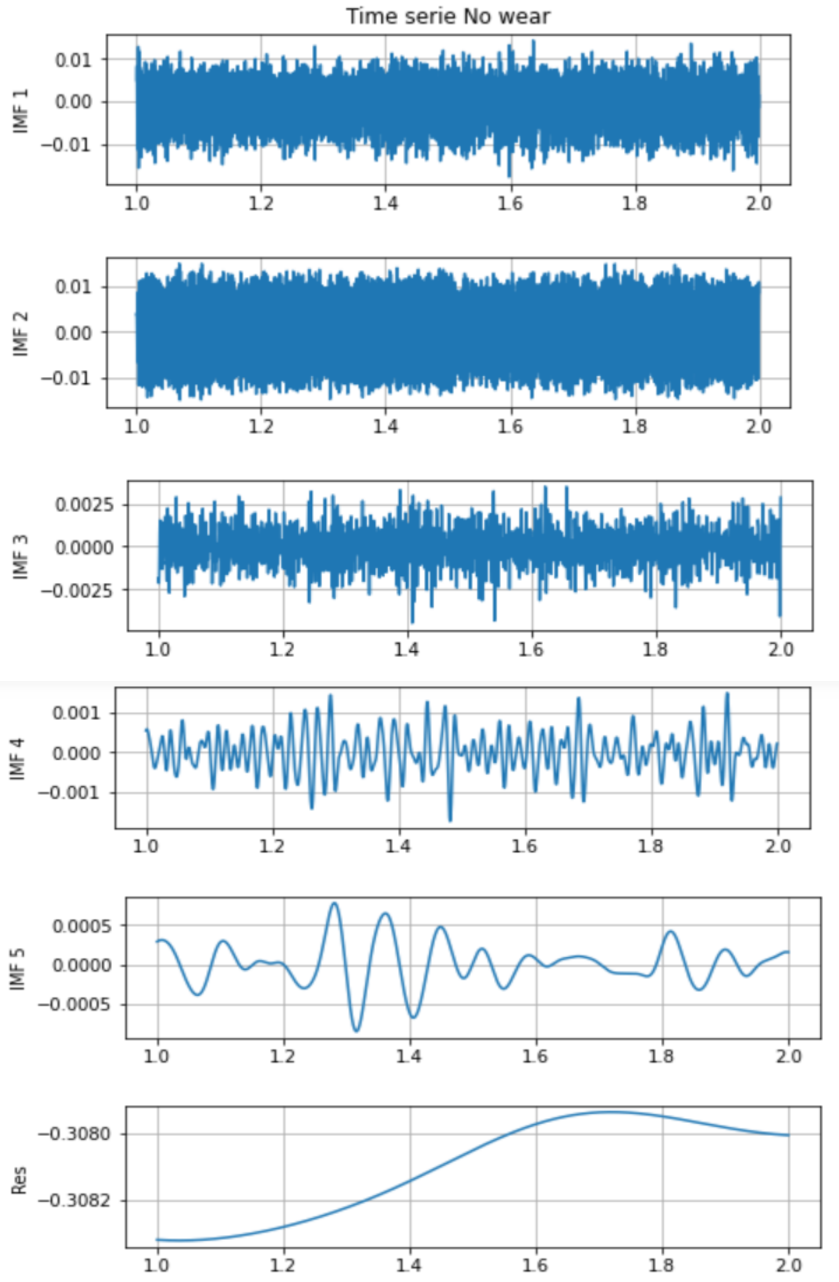

Figure 4. Decomposition of the signal into MFIs with the CEEMDAN method

In the CEEMDAN figure presented above, we have decomposed an original signal into IMFs. We have marked this:

- The decomposition is from high to low frequencies.
- As far as the decomposition of the IMF in the CEEMDAN method is concerned, we find IMF5, from IMF 1 to IMF 2, which are high frequency signals that are not useful. The low frequency signals start from IMF3 to IMF5 which are information carriers. Of these three low frequency IMFs we used IMF3 as our information carrier signal.
- The residual is almost zero (-0.3080 to -0.3082) which reflects an estimation error between the signal and the components.

3.2. Comparison of the EEMD method with the CEEMDAN method

In this section we have calculated the RMS as a function of the number of trials N_e necessary for a perfect decomposition of the original signal by the EEMD and CEEMDAN methods. The results of the statistical indicator RMS as a function of the number of trials N_e are shown in figure 5 in the case of the decomposition of the test signal by the EEMD method, and in figure 6 in the case where the CEEMDAN method was used for the decomposition. In order to have an EEMD decomposition with a very low error, a very large number of N_e tests are required.

The comparison of figures 5 and 6 shows that the number of trials N_e =500 the value of the mean square error in the EEMD method is RMS = 0.025. On the other hand in the CEEMDAN method the value of the statistical indicator RMS for the same number of trials N_e=500 is RMS = 0.0080.

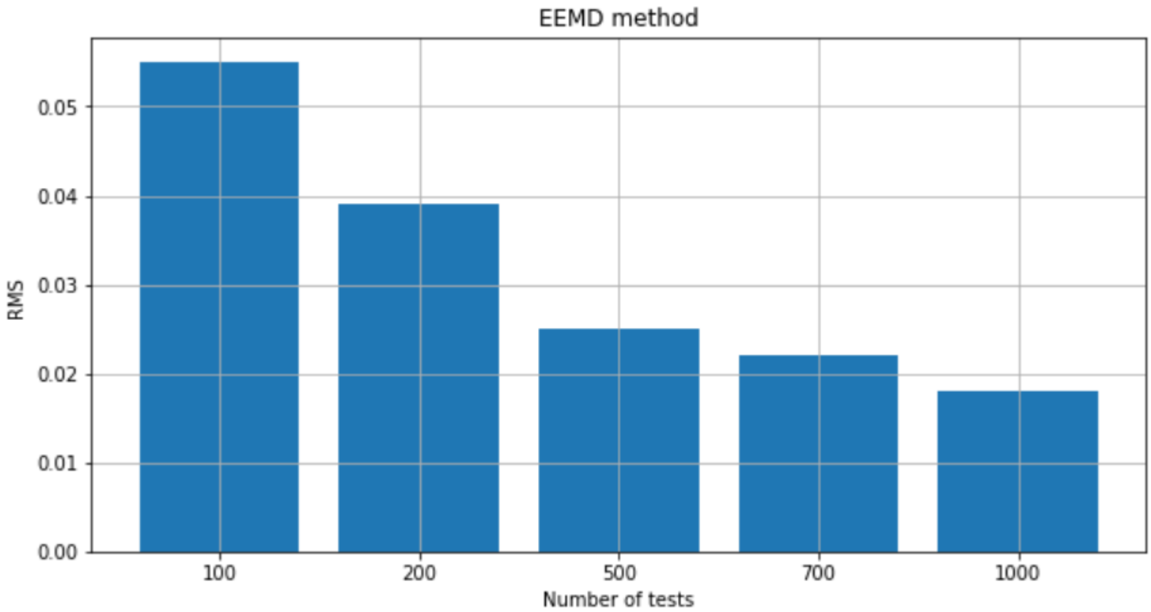

Figure 5. RMSE as a function of the number of trials N_e of the EEMD decomposition.

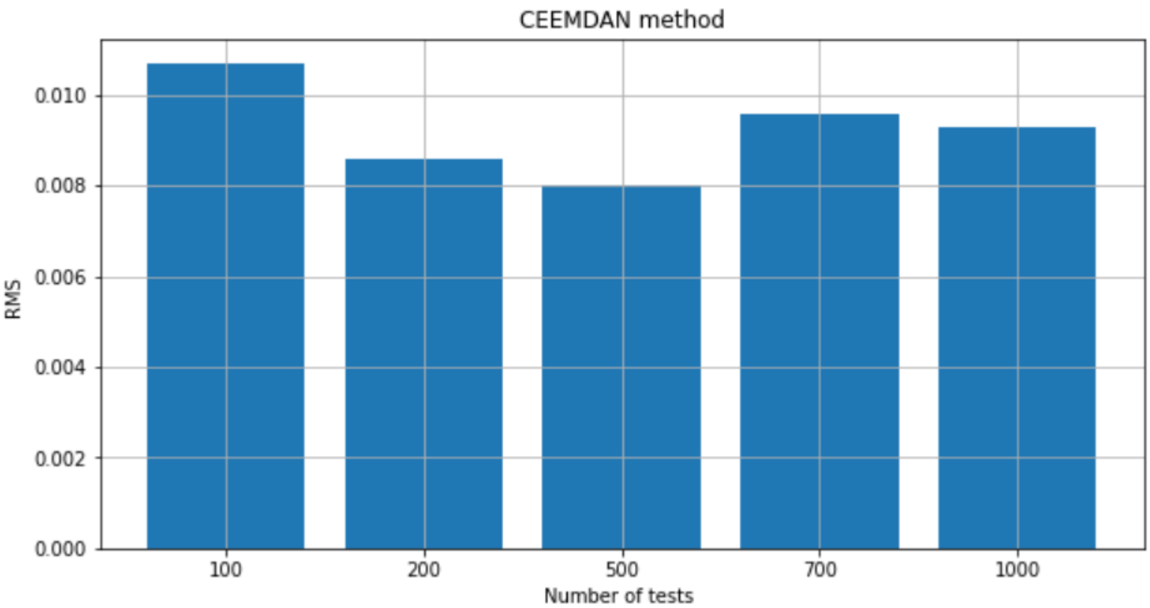

Figure 6. RMSE as a function of the number of trials N_e of the CEEMDAN decomposition

We have compared the number of tests of the decompositions by the EEMD and CEEMDAN methods, for the CEEMDAN method a number of tests $N_e = 500$ allowing to realize the best decomposition, whereas in the case of the EEMD method the best decomposition is realized with a number of tests N_e =1000.
From the point of view of the number of trials, we can conclude from these results that the CEEMDAN method is more efficient than the EEMD method. For we have detected an improvement of 50%.

Table 1. Comparison of the number of tests N_e between the EEMD and CEEMDAN methods.

Parameter	EEMD	CEEMDAN
N_e	1000	500
RMS	0.025	0.0080

4. CONCLUSION

In this study, we have compared the performance of the EEMD and CEEMDAN algorithms for non-linear signal processing. Our results demonstrate that the CEEMDAN algorithm provides a 50% improvement over the EEMD method in terms of the Root Mean Square and computation time.

The CEEMDAN algorithm was proposed as an improvement to the EEMD method, which was designed to solve the mode mixing problem present in the original EMD method. However, the EEMD method relies on a large number of trials, which can be a major drawback. In contrast, the CEEMDAN method was proposed to solve the problem of large computation time, which is also an important consideration in practical applications.

Our findings confirm the superiority of the CEEMDAN algorithm over the EEMD method for non-linear signal processing. This suggests that researchers and practitioners in this field should consider using the CEEMDAN algorithm when dealing with non-linear and non-stationary signals.

In conclusion, the CEEMDAN algorithm, published in 2011, is certainly a valuable improvement to the EEMD method. Further research may be needed to investigate the performance of these methods on different types of signals and to identify areas for further improvements.

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