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CEEMD-DFA and Variance Criterion Based De-noising Method Applied to Magnetic Resonance Sounding

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SUMMARY

One of the most important tasks in magnetic resonance sounding (MRS) is the noise removal prior to the signal extraction process. In this work a new time-domain method based a non-linear adaptive decomposition technique called complete ensemble empirical mode decomposition (CEEMD) in conjunction with a statistical optimization process for enhancing the signal-to-noise ratio of the MRS signal is developed. The filtering scheme starts with applying the CEEMD method to decompose the noisy MRS signal into a finite number of intrinsic mode functions (IMFs). Afterwards, a threshold region based on de-trended fluctuation analysis (DFA) is defined to identify the noisy IMFs, and then the no-noise IMFs are used to recover the partially de-noised signal. In the second stage, we applied a statistical method based on the variance criterion to the signal derived from the initial phase to remove the remaining noise. To demonstrate the functionality of the proposed strategy, the method was evaluated on an added-noise synthetic MRS signal, and on field data. The results show that the proposed procedure allows us to improve the signal to noise ratio significantly, and consequently, extract the signal parameters from noisy SNMR data efficiently

Key words: Magnetic Resonance sounding; Complete Ensemble Empirical Mode Decomposition; De-trended Fluctuation Analysis; Noise

INTRODUCTION

The magnetic resonance sounding (MRS) technique is a non-invasive hydro-geophysical tool, which as opposed to other geophysical approaches provides a direct measure of the water content with depth, but also indirectly the mean pore size of the aquifer (Hertrich, 2008). However, one of the major limitations of the MRS method is electromagnetic interferences. The MRS signal usually varies between ten to a couple of thousand nV and the ambient noise is often higher. Noise can be natural and caused by magnetic storms, thunderstorms etc., or man-made, generated by power lines, cars, electrical fences etc. Industrial noise is considered to be a superposition of harmonics of the industrial frequency 50 or 60 Hz. The MRS signal is strongly affected by noise and different procedures can be employed to eliminate or at least decrease the influence of noise during acquisition and data processing (Legchenko, 2007). Despite the significant data processing and hardware developments (see e.g., Jiang et al., 2011; Walsh et al., 2011; Falahsafari et al., 2014; Muller-Petke and Costabel, 2014; Ghanati et al., 2014; Dalgaard et al., 2014; Ghanati and Fallahsafari, 2015) since the advent of SNMR, the application at industrial and urban regions is greatly impossible. Typical signal amplitudes of MRS measurements are very weak and cannot be readily increased relative to the ambient noise level. Hence, it is essential to apply robust data processing approaches to the noisy and very weak MRS signals. The aim of this study is to tackle the application of a recent non-linear data analysis method, complete ensemble empirical mode decomposition (CEEMD), with the technique of statistical optimization process (Shahi et al. 2011) to retrieve the MRS signals. Moreover, de-trended fluctuation analysis (Peng et al. 1994) is used in the decomposition modes resulting from applying CEEMD to the signal to know whether a specific IMF contains useful information or primarily noise.

METHOD AND RESULTS

CEEMD algorithm

The EMD method self-adaptively decomposes a data series into a finite set of intrinsic mode functions (IMFs) form the highest and the lowest frequencies. Any IMFs should satisfy two specifications: 1) the number of maxima and minima and the number of zero crossings must either equal or differ by one at most; 2) at any given data, the mean value of the envelope defined by the local maxima and the envelope by the local minima should be zero. The IMFs are extracted based on an iterative process, called sifting. After extracting all IMFs, MRS signal $\mathrm{E(t)}$ can be expressed as

$$\mathrm{E(t)} = \sum_{k=1}^{M} \mathrm{IMF_k(t)} + \mathcal{R}_{\mathrm{M}}(\mathrm{t}), \qquad (1)$$

Where $\mathcal{R}_{\mathrm{M}}$ is the final residue, $\mathrm{IMF_k(t)}$ is kth IMF and M is the number of extracted IMFs.

For complicated signals, the major problem of the EMD algorithm is the mode mixing caused by the intermittency of signals, which renders the EMD unstable (Wu and Huang 2009). To relieve this drawback, ensemble empirical decomposition was suggested by Wu and Huang (2009).

The prime influence of decomposing through EEMD is that the added Gaussian white noises cancel each other in the final mean of the corresponding IMFs. This means that the IMFs stay within the natural dyadic filter widows, and thus appreciably lessen the chance of mode mixing and preserve the dyadic property. While EEMD provides great improvement over the EMD performance, there are deviations from IMFs because the IMFs in EEMD are mean value. Moreover, the EEMD algorithm bears the noise in the residue while reconstructing the signal. A variation of the EEMD algorithm, called complete ensemble empirical mode decomposition (CEEMD) was proposed by Torres et al. (2011) by which the original signal is fully reconstructed. Same as EEMD, the decomposition with the CEEMD algorithm is a noise-assisted method. A complete description of the concepts of IMFs and CEEMD is in Torres et al. (2011) and Ghanati et al. (2014). Decomposition of a signal using

CEEMD method leads to n-empirical modes and a residual, so that the higher frequencies are ordinarily found in the initial IMFs and lower frequencies in subsequent IMFs. The components with the higher frequencies carry clutter energy and contain noise.

De-trended Fluctuation Analysis (DFA) Criterion

The most critical point is to realize whether a specific IMF contains useful information or primarily noise. It should be noted that the noise appears in all IMFs, and that is hard to eliminate it by discarding just one specific IMF. In this section, a novel approach based on the de-trended fluctuation analysis (DFA) algorithm is presented for identifying noisy IMFs. A brief description of this technique is presented as follows:
For a given MRS signal $E(t_i)$, $t_i = i\Delta t$, $i = 1, \dots, K$, with sampling period Δt.

1- Compute the time series mean $\overline{E} = (1/K)\sum_{i=1}^{K} E(t_i)$.

2- Find integrated time series after removing the average $\overline{E}$ as

$$\psi(t_i) = \sum_{j=1}^{i}[E(t_i - \bar{E})] \;, \quad 1 \le i \le K \tag{4}$$

3- Divide the integrated time series $\psi(t_i)$ into N windows of length n.

4- For each window, Estimate local trend $\psi_n(t_i)$ by simply fitting a linear line.

5- Calculate the root-mean-square fluctuation F(n), by subtracting $\psi_n(t_i)$ from the integrated series $\psi(t_i)$ as

$$F(n) = \sqrt{(1/K)\sum_{i=1}^{K}[\psi(t_i) - \psi_n(t_i)]^2}, \quad i = 1, \dots, K. \tag{5}$$

6- Repeat steps 3-5, varying the window size between a minimum length of 5 samples and a maximum length of $K/4$ with K being the number of time series samples.

7- Draw a log-log plot of the root-mean-square fluctuation versus the corresponding window lengths resulting in a straight line with the slope of Φ, where Φ is called scaling exponent. The scaling exponent Φ can be regarded as an indicator of roughness. The larger value of Φ, the smoother is signal. In other words, small value of it signifies more rapid fluctuations (Mert and Akan 2014). Therefore, according to the above assumption, in this study, CEEMD based de-noising algorithm is implemented base on the use of DFA slope, φ as a threshold in order to distinguish the noisy IMFs. Consequently, a threshold region is defined as $\alpha = \Phi \pm 0.25$ where the region is defined based on the values of the scaling exponent corresponding to white Gaussian noise (0.5), pink noise (1.0) and Brownian noise (1.5). Note that the SNMR signals are primarily contaminated with harmonic and stochastic noises (e.g., white Gaussian noise and spiky events). At the first stage of the proposed method (i.e., CEEMD), we aim to mitigate white Gaussian noise by means of excluding the IMFs with Φ in the threshold region. Hence, based on the above description, the threshold region α is defined with $\Phi = 0.5$.

Statistical Optimization Process

The next algorithm implements SNMR signals de-noising in a statistical framework under an optimization problem, called variance criterion (Shahi et al., 2011) We initially express a brief review on MRS basics. MRS energizes the protons in groundwater by transmitting a resonance electromagnetic pulse with the Larmor frequency. The energized protons then generate a secondary magnetic resonance signal which is given by

$$E(t,q) = E_0(q) exp\,(-t/T_2^*(q)) cos\,(2\pi f_L t + \Theta(q)) \tag{2}$$

Where E_0 is the initial maximum voltage, T_2^* is the transverse relaxation time, f_L is the Larmor frequency and Θ is the phase shift between the returned signal and the excitation current.

The detection of the signal is realized by the synchronous detection technique. Mathematically, this procedure can be expressed as a multiplication with the complex term $2e^{j2\pi f_R t}$ (Levitt, 1997), which gives

$$E_{Multiplied}(t) = E_0\, exp\left(-\frac{t}{T_2^*}\right)[exp(j(2\pi f_R + 2\pi f_L)\,t + j\Theta_0) + exp(j(2\pi f_R - 2\pi f_L)\,t - j\Theta_0)], \tag{3}$$

after applying the low-pass filter, we get

$$E_{Detection}(t) = E_0\, exp\left(-\frac{t}{T_2^*}\right) exp(j(2\pi f_0 t - \Theta_0)) \tag{4}$$

The equation 4 indicates the ideal form of the MRS signal. But generally, this is not true and MRS signal is, in fact, contaminated with noise. Thus, the real noisy MRS signal can be expressed as follows.

$$E_{Detection}^{Noisy}(t) = E_0\, exp\left(-\frac{t}{T_2^*}\right)[exp(j(2\pi f_0 t - \Theta_0))] + \sum_K P_K exp\,(j2\pi f_K t + j\Theta_K) + e_{Complex}(t), \tag{5}$$

The second term of the above equation is related to the harmonic noise part and $e_{Complex}(t)$ denotes the stochastic noise part containing the background noise, and spiky events. Spiky signals appear randomly, so that these noise features are considered as parts of $e_{Complex}(t)$ (Strehl, 2006). The main objective is to remove the noise from equation 5 and access to equation 4. Noise cancellation from the MRS signal requires perception about the noise parameters and the ideal signal features. The mean or the area under the curve is an exclusive characteristic of these two components. The mean of two signals, i.e., the ideal signal and noise signal, is equal to the summation of the mean of each one. On the other hand, the mean of the real signal is equal to the summation of the mean values of the ideal signal and noise. Mathematically, this can be defined as

$$A = A_S + A_N \tag{6}$$

Where A denotes the area under the curve of the real signal, A_S is the area of the ideal signal of equation 5 and A_N is the noise area. As the mean value of the noise (or its area under the curve) is approximately zero (Strehl, 2006; Shahi et al, 2011), therefore the signal mean will not be changed after being noisy. considering the mentioned assumption, we get

$$E_0 = A/(1 - exp\,(-t/T_2^*))T_2^* \tag{7}$$

Whereas, NUMIS equipment records the noise automatically prior to the MRS measurement thus the parameters of the environment noise can be measured. Variance is one of such parameters which fully identified before the original signal record. Thus, comparison of the variance of the estimated and recorded noises makes possible to discern the precision of the values of E_0 as well as T_2^*. In order to achieve correct E_0 and T_2^*, an optimization problem based on the variance of the estimated and recorded noises is defined. The calculated variance is compared with the variance of the recorded noise in order to realize the E_0 variations, then the estimation and alteration of E_0 are continued until the difference between the variance of the estimated noise and the variance of the recorded noise will be approached to approximately zero. When E_0 is flawlessly approximated, we will be ensured that the value of T_2^* is accurate as well as the estimated ideal signal is considerably noiseless.

Numerical results

We first generate an exponentially decaying signal with initial amplitude $E_0 = 140$ nV and a decay time $T_2^* = 190$ ms. Then, three different noise levels which contain deterministic (i.e., harmonic noise) and stochastic (i.e., uncorrelated Gaussian distributed noise and spiky events) noises, with SNRs: 3.9, 5.07 and 9.6 dB, were added to the synthetic signal and the three methods CEEMD-DFA, variance criterion, and the combined CEEMD-DFA-variance criterion methods were used for de-noising. Figure 1 shows the simulated SNMR signal (SNR= 5.07 dB) contaminated with harmonics, spiky events and Gaussian noise with standard deviation $\sigma = 30$ nV and mean value $m = 0$. The noise cancelation is carried out in two stages here: the CEEMD method is just implemented at the first stage, at the second stage the variance criterion is implemented as well. Figure 2 shows the IMFs obtained from the decomposition of the synthetic SNMR signal. Also, the DFA scores of the corresponding IMFs are illustrated in Figure 3. As described in the previous sections, the IMFs which have lower fluctuation value Φ than the threshold α are identified as noisy components, and consequently, are not included into reconstruction. Thus the partial signal reconstruction is the sum of the IMFs from 4 to 8 which results in the de-noised signal shown in Figure 4. It can be seen that the harmonic and Gaussian noises as well as outliers have been considerably removed through the proposed CEEMD-DFA based de-noising algorithm. In addition, the signal-to-noise ratio increases from 5.07 dB (related to the noisy signal) to 21.14 dB. Afterwards, the signal obtained from the previous stage enters the variance criterion to cancel the remaining noise in the signal and estimate the concerning parameters. So, by implementing the second stage, the signal-to-noise ratio increases to 28 dB and the SNMR signal parameters E_0 and T_2^* are estimated 141 nV and 200 ms with mean squared error (MSE) 6.68 while the value of MSE obtained by using merely use of variance criterion is 16.27 (see Table 1). Figure 5 displays the outcome of applying the CEEMD-DFA filtering scheme and the proposed combined method to the simulated MRS signal (5.07 dB).

Table 1. Estimated parameters and SNR and MSE performance of variance criterion and joint application CEEMD-DFA and variance criterion.

	Signal (SNR=5.07 dB)			
Evaluation Parameters	**Est. E_0 (nV)**	**Est. T_2^* (ms)**	**SNR (dB)**	**MSE**
Variance Criterion	**143.1**	**206**	**24**	**16.27**
Integration of CEEMD-DFA with Variance Criterion	**141**	**200**	**28**	**6.69**

CONCLUSIONS

We presented a novel method for reducing stochastic and harmonic noises from SNMR signals, integrating the de-trended fluctuation analysis (DFA) thresholded complete ensemble empirical mode decomposition (CEEMD) with statistical optimization process through variance criterion. We initially applied a recent developed procedure called DFA to the decomposition modes resulting from the CEEMD algorithm in order to distinguish the noise components and noise free signal components. Based on a predefined threshold region, the IMF(s) having lower DFA score (scaling exponent) than the threshold are excluded in the reconstruction phase to obtain partially de-noised version of the signal. Subsequently, the variance criterion is applied to the obtained signal from the previous stage to remove the remaining noise. The results of numerical experiments showed quite reasonable performance of the proposed combined method compared to merely use of CEEMD or variance criterion in noise cancellation that finally leads to more accurate and reliable recovery of the signal parameters.

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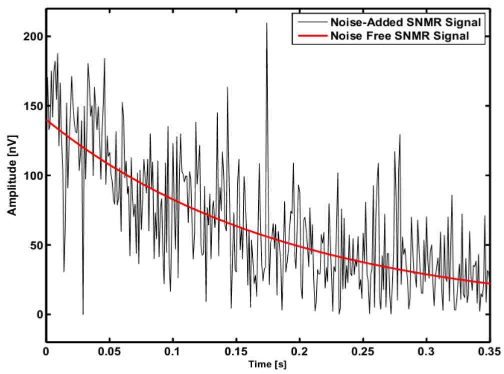

Figure 1. Noise free (red) and Noise-added SNMR signal (black) with SNR $= 5.07$ dB.

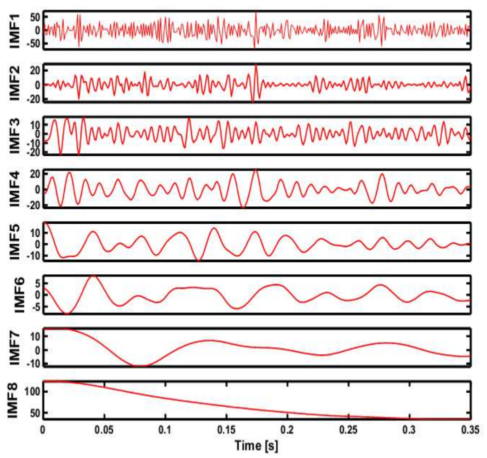

Figure 2. Illustration of resulting IMFs after Complete Ensemble Empirical Mode Decomposition of the noise-added SNMR signal shown in fig 1.

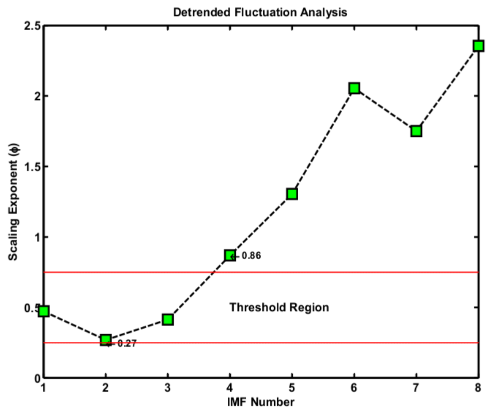

Figure 3. DFA scores (scaling exponent) of the IMFs resulting from applying CEEMD to the simulated signal shown in Fig. 2.

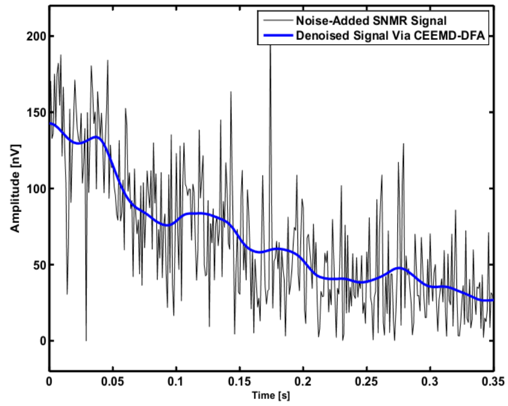

Figure 4. Noise-added SNMR signal (black) with SNR $=$ 5.07 dB and de-noised signal from CEEMD-DFA (blue) with SNR $= 21.14$ dB.

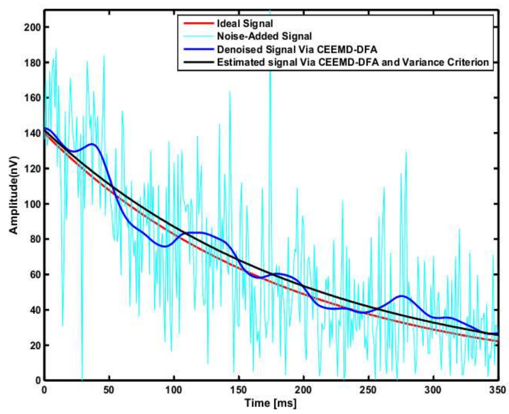

Figure 5. Noise free signal, Noise-added SNMR signal (SNR $= 5.07$ dB), de-noised signal from CEEMD-DFA (SNR $= 21.14$ dB) and estimated signal using CEEMD-DFA and variance criterion (SNR $= 28$ dB) with $T_2^* = 200$ and $E_0 = 141$.