Evaluating three different adaptive decomposition methods for EEG signal seizure detection and classification

Vinícius R. Carvalho* [2,3], Márcio F.D. Moraes [1,3], Antônio P. Braga [2], Eduardo M.A.M. Mendes [1,2,3]

1 - Centro de Tecnologia e Pesquisa em Magneto-Ressonância, Escola de Engenharia, Universidade Federal de Minas Gerais, Av. Antônio Carlos, 6627, Pampulha, 31270 901, Belo Horizonte, Minas Gerais, Brasil

2 - Programa de Pós-Graduação em Engenharia Elétrica, Universidade Federal de Minas Gerais, Av. Antônio Carlos, 6627, Pampulha, 31270 901, Belo Horizonte, Minas Gerais, Brasil

3 - Núcleo de Neurociências, Departamento de Fisiologia e Biofísica, Instituto de Ciências Biológicas, Universidade Federal de Minas Gerais, Av. Antônio Carlos, 6627, Pampulha, 31270 901, Belo Horizonte, Minas Gerais, Brasil

*Corresponding Author:

Vinícius Rezende Carvalho

Programa de Pós-Graduação em Engenharia Elétrica

Universidade Federal de Minas Gerais

Av. Antônio Carlos 6627, 31270-901

Belo Horizonte, MG, Brazil.

Phone: 55 31 3409-2930

Fax: 55 31 3409 29 24

Email: vrcarva@ufmg.br

Abstract

Signal processing and machine learning methods are valuable tools in epilepsy research, potentially assisting in diagnosis, seizure detection, prediction and real-time event detection during long term monitoring. Recent approaches involve the decomposition of these signals in different modes or functions in a data-dependent and adaptive way. These approaches may provide advantages over commonly used Fourier based methods due to their ability to work with nonlinear and non-stationary data. In this work, three adaptive decomposition methods (Empirical Mode Decomposition, Empirical Wavelet Transform and Variational Mode Decomposition) are evaluated for the classification of normal, ictal and inter-ictal EEG signals using a freely available database. We provide a previously unavailable common methodology for comparing the performance of these methods for EEG seizure detection, with the use of the same classifiers, parameters and spectral and time domain features. It is shown that the outcomes using the three methods are quite similar, with maximum accuracies of 97.5% for Empirical Mode Decomposition, 96.7% for Empirical Wavelet Transform and 98.2% for Variational Mode Decomposition. Features were also extracted from the original non-decomposed signals, yielding inferior, but still fairly accurate (95.3%) results. The evaluated decomposition methods are promising approaches for seizure detection, but their use should be judiciously analysed, especially in situations that require real-time processing and computational power is an issue. An additional methodological contribution of this work is the development of two python packages, already available at the PyPI repository: One for the Empirical Wavelet Transform (ewtpy) and another for Variational Mode Decomposition (vmdpy).

Keywords

EEG

Empirical mode decomposition

Empirical wavelet transform

Variational mode decomposition

Seizure detection

Signal processing

Machine learning

1 Introduction

2   Epilepsy is a burdening neurological disease that has a prevalence rate of around 6 per 1000 persons

3   and incidence rate of 61 per 1000 person-years [1]. One of the factors contributing for its high incidence

4   rate is the large number of causes leading to this condition, such as: genetic predisposition, displasias,

5   cerebrovascular disease (CVD), trauma, tumor, infection, ischemia, among others [2].

6   Recurrent seizures are considered the hallmark of Epilepsy. These events reflect the abnormal firing

7   of groups of neurons in the brain, in general synchronous and of high intensity [3]. This deviation from

8   the normal functioning patterns of neurons may invoke sensations varying from strange feelings,

9   behaviors and sensations to seizures with muscular spasms and possible loss of conscience [4].

10   The electroencephalogram (EEG) is a high temporal resolution recording of brain electrical activity

11   central to the diagnosis of epilepsy and other neurological disorders. Its signals can reflect abnormal

12   neuronal activity during ictal (i.e. seizures) or interictal periods, such as sharp transients occurring in-

13   between seizures [5]. These signals are commonly interpreted by experienced neurologists through

14   visual inspection, taking into account features such as frequency, amplitude and regularity of waveforms,

15   reactivity to stimuli, spatial range and temporal persistence of the signal's anomalies [6]. However, this

16   method may be cumbersome and time consuming, especially for long series and multi-channel data;

17   which can lead to an increasingly high ratio of false-negative results. Furthermore, there is a series of

18   subtle signal features and components, as well as inter-channel relationships, which are virtually

19   impossible to detect by simple visual inspection. This task may be assisted by signal processing and

20   classification algorithms [7] that can deal with signal nonlinearities and subtleties, high-dimensional data

21   and the possibility of real-time processing. As such, these automated methods are valuable tools for the

22   diagnosis, detection and prediction of epilepsy and epileptic seizures [8].

23   A variety of algorithms and signal processing techniques have been developed for the extraction of

24   relevant features related to the epileptic phenomena [9]. Methods which analyze frequency components

25   using the Fourier Transform are not always recommended, because EEG signals contain non-stationary

26   components, violating conditions for the use of such transform [10]. Thus, recent methods for EEG

27   analysis of epileptic patients may use Time-Frequency approaches, or non-linear methods such as

28   Lyapunov Exponents, Fractal Dimension, Entropy or Correlation Dimension [11]. Other methods include

29   the use of signal decomposition in adaptive ways, such as the Empirical Mode Decomposition (EMD),

30   proposed by Huang et al [10].

31   Of particular interest to the work presented here, the EMD is an adaptive and data-dependent

32   decomposition method that successively extracts intrinsic mode functions (IMFs), defined by amplitude

33   modulated (AM) and frequency modulated (FM) components. Accordingly, complex non-linear and non-

34   stationary signals can be decomposed into a finite number of IMFs, each with well-behaved Hilbert

35   Transforms [10]. The EMD approach, as well as its extensions [12,13], has been successfully used in

36   epilepsy [14–17]. However, drawbacks such as computational cost, lack of theory (due to its algorithmic

37   approach) and difficulty in interpreting the large number of modes have motivated the use and evaluation

38   of different adaptive decomposition methods in seizure EEG signals [18].

39   The Empirical Wavelet Transform (EWT) [18] addresses some limitations of EMD. By adapting

40   some of the Wavelet formalisms, this method designs appropriate wavelet filter banks and decomposes a

41   signal into a predetermined number of modes. The use of EWT has been explored in different areas such

42   as compression of electrocardiogram (ECG) signals [19], decomposition of seismic activity [20] and

43   time-frequency representation of non-stationary signals [21]. Although the use of Wavelets for seizure

44   detection and classification has been widely explored [6,22–24], few works evaluate EWT for processing

45   seizure EEG signals [25,26].

46   Another adaptive method denominated Variational Mode Decomposition [27] (VMD) decomposes a

47   signal into its principal modes adaptively and non-recursively. The method is related to the so-called

48   Wiener filter, a property which grants it advantages in relation to noise robustness. Similar to what

49   happened in the case of EWT, few researchers have evaluated VMD use for seizure EEG analysis [28–

50   30].

51   When processing EEG from ictal phenomena, features generated from the use of the aforementioned

52   decomposition methods are promising tools. In addition to their adaptive capabilities and ability to deal

53   with nonlinear and non-stationary signals, extracted modes (or signal components) are compact around

54   specific center frequencies and have well-behaved Hilbert transforms. This enables the extraction of

55   features related to amplitude or bandwidth modulation, as well as instantaneous phase and amplitude.

56   This work aims to compare these three decomposition methods for EEG signal seizure detection using a

57   freely available database and a common methodology, by extracting the same features and using the same

58   classifiers. So far, this comparison has been hampered not only by the small number of works using EWT

59   and VMD, but also by the fact that, for seizure detection, EMD, VMD and EWT are evaluated in the

60   literature using different sets of features, parameters and classifiers. In this work, results are also

61   compared with features extracted from original non-decomposed signals. Expected results are

62   performance improvements with the use of adaptive decomposition methods (EMD, EWT and VMD), but

63   similar overall performances among them.

64   The rest of this work is organized into three sections. In Section 2, the used methodology is

65   presented, containing the used data, decomposition methods, description of extracted features and

66   classification problem. In Section 3, the obtained results are presented and discussed. Concluding remarks

67   are left for the last section.

Methods

Dataset

70   The EEG data used in this work was obtained from a public online database offered by the University

71   of Bonn. This dataset is divided into 5 subsets: *Z, O, N, F, S* (or A, B, C, D, E) [31]. Each subset contains

72   100 temporal series with sampling frequency of 173.6 Hz and duration of 23.6 seconds. The Z and O

73   subsets correspond to surface EGG recordings of 5 healthy volunteers, with eyes open and closed,

74   respectively. The rest of the subsets belong to presurgical recordings of epileptic patients. Set S contains

75   seizure activity, while sets F and N are from seizure-free intervals, with electrodes placed on the

76   epileptogenic zone and opposite hippocampus, respectively.

77   This work deals with the most common classification problem, using three subsets: S, F and N,

78   corresponding to Ictal, Interictal and Normal classes, respectively. Samples from each class and their

79   regularized spectra, given by the Gaussian-filtered Fast Fourier Transform (FFT) of each signal are shown
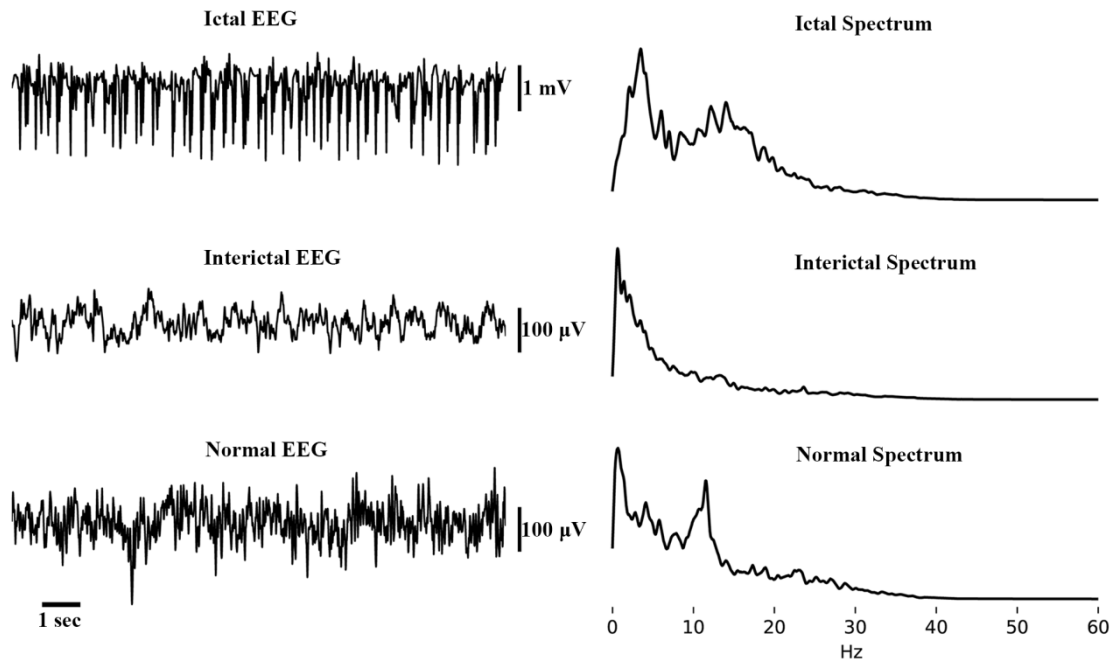
80   in **Erro! Fonte de referência não encontrada.**.

81

82   **Fig 1.** Example EEG signals of each class (Ictal, Interictal and Normal) and respective spectra

83   The first stage of processing consists of applying a zero-phase 4th order lowpass Butterworth filter,

84   with cutoff frequency equal to 40 Hz. Next, signals are decomposed into N modes or IMFs, either by

85   EMD, EWT or VMD, which are described in the following sections.

86 # Empirical Mode Decomposition

87   The Empirical Mode Decomposition (EMD) is an interesting method due to its adaptability, not

88   depending on assumptions as linearity or stationarity. This method aims to divide the analyzed signal into

89   a series of Intrinsic Mode Functions (IMFs), where each IMF must satisfy to two relatively simple

90   conditions:

91

92   I. The number of extrema must be equal or differ by at one (at most) in relation to the number

93   of zero crossings.

94   II. In every sample, the mean envelope value, defined by the local maxima and minima, must

95   be equal to zero.

96 The algorithm proposed by [10] for obtaining IMFs consists of the following steps:

97   1) Given a temporal series $x(t)$, find the local maxima and minima.

98   2) Generate the envelopes e_{max} and e_{min} by cubic spline interpolation of maxima and minima,

99   respectively.

100   3) Calculate the mean of the envelopes, $m_i(t) = (e_{max}(t) + e_{min}(t))/2$

101   4) Subtract the value found previously from the: $h(t) = x(t) - m_i(t)$. If $h(t)$ satisfies the

102   conditions given previously for an IMF, an IMF $c_i(t) = h(t)$ is found.

103   5) A new residue r is generated: $r(t) = x(t) - c_i(t)$. Repeat steps 1 to 4, applied to the

104   residue r, in order to find the remaining IMFs. The process halts when it is no longer

105   possible to compute an IMF from a residue, which is then defined as a final residue r_M.

106 The signal is then decomposed into a determined number of IMFs $c_i(t)$, plus another residue r_M, and

107 represented by (1),

$$x(t) = r_M + \sum_{i=1}^{N} c_i(t), \tag{1}$$

108 where N is the total number of IMFs found.

109 Unlike methods such as the Discrete Wavelet Transform, which extracts low frequencies (or

110 approximations) first, and detail levels (corresponding to higher frequencies) later, the first modes

111 isolated by EMD correspond to high frequencies of the signal, then moving progressively to slower

112 components.

113 The pyEMD Python package [32] was used for the implementation of EMD in this work.

Empirical Wavelet Transform

114

115 As in EMD, EWT method aims to extract the oscillatory amplitude (AM) and frequency (FM)

116   components of a signal, considering these as having compact Fourier support. Unlike traditional wavelet

117   transforms, which use predefined filter bank structures, EWT defines the supports of the filters in

118   accordance with the spectral distribution of the signal, in a fully adaptive way. Some considerations are

119   made for analysis: (1) the signal must be real valued, due to the need for symmetry, and (2) a normalized

120   frequency axis with 2π periodicity is considered, but analysis is restricted to $[0, \pi]$, due to Shannon's

121   sampling criterion.

122   A number of modes N is defined a priori, determining how many segments the spectrum is

123   partitioned in the range $[0, \pi]$. Among the N+1 frequency limits to be determined, two are already

124   predefined (ω_0 and ω_N), corresponding to frequencies of 0 and π, respectively. The remaining N-1 limits

125   are set according to the distribution of the signal's frequency spectrum: the N-1 local maxima are found,

126   and the limits ω_n (n = 1,2, .. N-1) are defined as midpoints between two consecutive maxima. In this

127   work, maxima were detected on the smoothed spectrum that is obtained by applying a Gaussian filter

128   (filter length = 25, σ = 5) on the Fast Fourier Transform of each signal. The segmentation of a signal

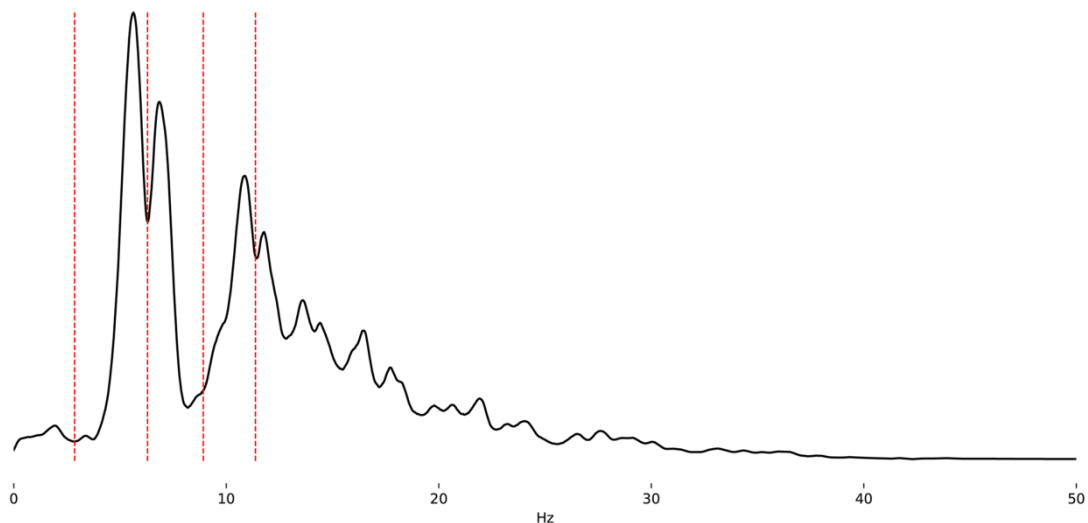129   spectrum into 5 Modes is given in **Erro! Fonte de referência não encontrada.**.

131   **Fig 2.** Spectral segmentation of ictal EEG into 5 modes

133   With limits ω_n defined, the segments $\Lambda_n = [\omega_{n-1}, \omega_n]$ fill the interval $[0, \pi]$. The limits of each segment

134   are characterized by a transition period centered at the respective ω_n, with width equal to $2\tau_n$. Each

135   segment is associated to a filter (lowpass for the ω_0, bandpass for the rest), the construction of which is

136   related to Littlewood-Paley and Meyer Wavelets [33]. Thus, an empirical scale function $\phi_n(\omega)$ and an

137   Empirical Wavelet $\psi_n(\omega)$ are defined. These are constructed in such a way that a Tight Frame is

138   obtained. Further details on the construction of such functions are given in [18].

139   With the conditions for building a Tight Frame satisfied, the EWT is defined similarly as the

140   traditional Wavelet Transform, with details given by the inner product of the Wavelet function with the

141   signal, and the approximation equal to the inner product of the signal with the scaling function.

142   Based on Jérôme Gilles' MATLAB toolbox [34], a Python package of EWT (ewtpy) was developed

143   for this work and is available at https://pypi.org/project/ewtpy/ and at https://github.com/vrcarva/ewtpy.

Variational mode decomposition

145   In the Variational mode decomposition, the number of modes is predefined. Initially, the method

146   assumes each mode k as having compact bandwidth in the Fourier spectrum, with a respective central

147   frequency ω_k. For each mode, a unilateral frequency spectrum is obtained and shifted to baseband

148   according to its estimated central frequency. The bandwidth is then assessed by the H^1-norm Gaussian

149   smoothness of the demodulated signal, with the optimization problem iteratively updating each mode in

150   the frequency domain. The complete constrained variational optimization problem is available in [27].

151   In comparison with EMD, VMD performed better in tests dealing with tone detection and separation,

152   and noise robustness [27]. And although its use for long-time EEG signals suffers from caveats due to

153   non-stationarity, the use of VMD in this work is motivated by the relatively short duration of the EEG

154   signals from the used Database, and the focus on classification rather than exact mode decomposition and

155   reconstruction.

156   A Python package, based on the original MATLAB toolbox [35], was developed for this work and

157   made available at https://pypi.org/project/vmdpy/ and at https://github.com/vrcarva/vmdpy. These can be

158   readily installed with pip (*pip install vmdpy* and *pip install ewtpy*).

Hilbert Transform and Analytic signal

160   The presented decomposition methods have the interesting property of yielding modes/IMFs with

161 "well-behaved" Hilbert transforms [10,27], from which features as instantaneous phase, frequency or

162 envelope can be extracted. The analytic signal of each mode/IMF is given by equation (2).

$$z(t) = x(t) + jx_h(t) = A(t)e^{j\varphi(t)} \qquad (2)$$

163 where $x_h(t)$ is the Hilbert transform of $x(t)$,

$$x_h(t) = x(t) * \frac{1}{\pi t} \qquad (3)$$

164 and the amplitude and phase are defined as:

$$A(t) = \sqrt{x^2(t) + x_h{}^2(t)} \qquad (4)$$

$$\varphi(t) = \arctan\left(\frac{x(t)}{x_h(t)}\right) \qquad (5)$$

165   The instantaneous frequency of a given IMF can be calculated from its analytic signal with:

$$\omega(t) = \frac{d\varphi(t)}{dt} \qquad (6)$$

166   By dividing a signal into a given number of modes/IMFs, features related to their respective analytic

167 signals and spectra can be extracted.

Feature extraction

169   Modes given by the three aforementioned methods (EMD, EWT and VMD) may be considered as

170 amplitude and frequency modulated signals. Thus, feature extraction is made according to properties of

171 the spectrum of each mode, with a similar approach used by [36] and [15].

172   The first feature extracted is the Spectral Energy (SE), given by Equation 7.

$$SE = \frac{1}{N}\sum_{f=0}^{\frac{f_s}{2}} P_{XX}(f), \qquad (7)$$

173 where N is the total number of spectral coefficients, and P_{XX} is the mode PSD estimated by Welch's

174 method [37]. The second feature is the Spectral Entropy (SEnt), shown in Equation 8.

$$SEnt = -\sum_{f=0}^{\frac{f_s}{2}} \bar{P}_{XX}(f)\log[\bar{P}_{XX}(f)] \tag{8}$$

175     $\bar{P}_{XX}$ is the normalized PSD. The following three features are related by the main frequency

176   component of the respective mode. After determining the global maximum of P_{XX}, the corresponding

177   magnitude is defined as the Spectral Peak (SP), as well as the associated frequency (f), defining the 3rd

178   and 4th features. The following feature is the spectral centroid (SC) of the respective mode, defined in

179   Equation 9:

$$SC = \frac{\sum_{f=0}^{\frac{f_s}{2}} \omega(f)M(f)}{\sum_{f=0}^{\frac{f_s}{2}} M(f)}, \tag{9}$$

180   where f is the frequency bin, and $\omega(f)$ and $M(f)$ are respectively, the central frequency and magnitude of

181   the PSD of bin f. The last two features are the AM and FM bandwidths, defined by Equations 10 and 11

182   [38]:

$$B^2{}_{AM} = \frac{1}{E}\int\left(\frac{dA(t)}{dt}\right)^2 dt \tag{10}$$

$$B^2{}_{FM} = \frac{1}{E}\int\left(\frac{d\phi(t)}{dt} - \langle\omega\rangle\right)^2 A^2(t)dt, \tag{11}$$

183   where A is the amplitude of the analytic signal, E is the Energy and $\langle\omega\rangle$ is the center frequency of the

184   current mode, given by Equation 12.

$$\langle\omega\rangle = \frac{1}{E}\int\frac{d\phi(t)}{dt}A^2(t)dt \tag{12}$$

185   Time-domain features are also extracted from each mode: Hjorth parameters [39] and statistical

186   moments.

187   Hjorth Mobility is related to the mean frequency of the signal and proportional to the variance of its

188   spectrum, while Hjorth Complexity is an estimate of the signals' bandwidth [40]. These are defined by:

$$Mob(x) = \sqrt{\frac{Var\left(\frac{dx(t)}{dt}\right)}{Var(x(t))}} \tag{13}$$

$$Comp(x) = \frac{Mob\left(\frac{dx(t)}{dt}\right)}{Mob(x(t))}, \qquad (14)$$

189   where $x(t)$ is the current signal component, and Var() is the variance.

190   The Skewness is related to the signal distribution's asymmetry, and is given by the following

191   equation:

$$S(x) = E\left[\left(\frac{x(t)-\mu}{\sigma}\right)^3\right] \qquad (15)$$

192   The standard deviation of $x(t)$ is represented by σ, and its mean by μ. The Kurtosis is related to the

193   tails of the distribution yielded by the signal and is given by.

$$S(x) = E\left[\left(\frac{x(t)-\mu}{\sigma}\right)^4\right] \qquad (16)$$

Feature selection and classification

195   For feature selection and classification algorithms, functions from scikit-learn package [41] were

196   used.

197   Since the number of extracted features of each signal is relatively large, and not every feature is

198   relevant for class discrimination, there is a need for a feature selection or ranking method. In this work, 15

199   features were selected according to the SVM Recursive Feature Elimination (RFE) [42]. Afterwards,

200   different classification methods were evaluated: k-nearest neighbors (KNN) [43], Linear and Radial Basis

201   Function (RBF) Support Vector Machines (SVM) [44], Gaussian process classification (GPC) based on

202   Laplace approximation [45] and a Multi-layer Perceptron (MLP) [46].

203   In order to avoid data overfitting, 5-fold cross-validation was used for the classification algorithms,

204   with 70% of samples used for Training, and 30% for testing. For performance evaluation, four common

205   measures were employed; Accuracy (ACC), Specificity (SPEC), Sensitivity (SEN) and Area Under the

206   Receiver Operating Characteristic (ROC) curve (AUC). The last three measures are calculated by

207   choosing the ictal class as positive.

Results and discussion

208

209   All scripts used in this work are available online at https://github.com/vrcarva/carvalho-etal-2019.

210   **Fig 3** illustrates the decomposition of a seizure EEG by EMD, EWT and VMD. Fig S1, and Fig S2

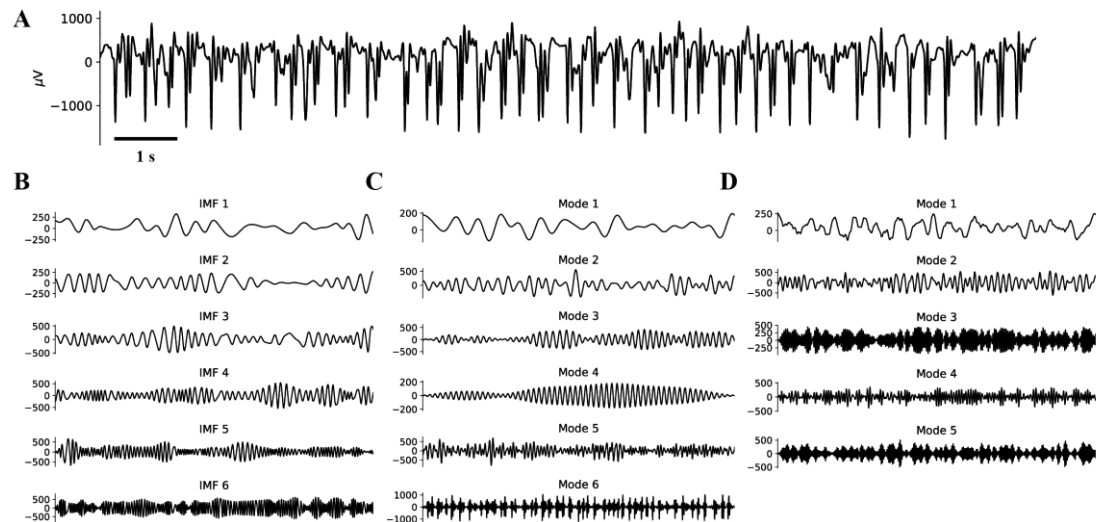211   show this for inter-ictal and normal signals, respectively.

212

213   **Fig 3. Decomposition of ictal EEG**. (A) Original non-decomposed signal. (B) First six extracted

214   IMFs with EMD. (C) 6 components extracted with EWT. (D) 5 components extracted with VMD.

215   Samples of each class were decomposed by EMD, EWT or VMD, into N (4, 5, 6 and 7) Modes,

216   followed by the extraction of the 11 features of each one, thus resulting in N*11 features for each sample.

217   The SVM-RFE algorithm then selected 15 of these features. RFE was not applied for the "control" (the

218   non-decomposed signal), which results in 11 features for each sample. Afterwards, different classifiers

219   are trained and tested, resulting in performance evaluation metrics. Ten iterations of training/testing were

220   accomplished, resulting in mean ± standard deviation for each performance parameter. The best results

221   for each classifier applied to each decomposition method are shown in Table 1.

222

223 **Table 1: Classification results of different decomposition (EMD, EWT, VMD**
224 **and original signal) and classification methods.**

METHOD	MODES	MEASURE	KNN	LINEAR SVM	RBF SVM	GPC	MLP
EMD	6	AUC (%)	99.00±0.28	99.25±0.22	99.63±0.11	99.72±0.08	99.55±0.14
		ACC (%)	97.10±0.63	95.90±0.33	97.53±0.22	97.0±0.58	96.80±0.34
		SEN (%)	94.20±1.60	94.10±0.83	98.60±0.49	96.2±0.98	95.10±0.94
		SPEC (%)	99.05±0.35	97.30±0.24	97.50±0.22	97.9±0.58	98.15±0.23
EWT	6	AUC (%)	96.97±0.61	99.27±0.08	99.35±0.09	99.32±0.17	99.43±0.10
		ACC (%)	93.80±0.93	95.77±0.42	96.60±0.70	95.93±0.51	96.70±0.38
		SEN (%)	92.60±1.36	94.50±1.02	96.00±0.63	95.6±1.20	95.80±1.08
		SPEC (%)	94.40±1.04	96.45±0.35	97.20±0.40	96.55±0.47	97.60±0.44
VMD	5	AUC (%)	98.17±0.31	99.25±0.18	99.27±0.11	99.49±0.19	99.41±0.10
		ACC (%)	96.83±0.37	96.90±0.40	98.20±0.31	97.50±0.50	97.67±0.42
		SEN (%)	95.90±1.30	95.80±0.87	97.40±0.49	96.60±0.80	95.70±0.64
		SPEC (%)	97.70±0.46	97.85±0.45	98.65±0.39	98.45±0.57	98.85±0.23
-	1	AUC (%)	97.31±0.51	96.93±0.31	98.24±0.29	98.36±0.31	98.12±0.28
		ACC (%)	93.27±0.79	89.87±0.65	92.60±0.42	95.27±0.73	93.27±0.51
		SEN (%)	91.10±1.76	89.00±0.63	88.70±1.55	93.60±1.20	89.70±0.90
		SPEC (%)	94.85±1.10	90.80±0.81	95.05±0.52	96.10±0.66	95.50±0.84

225

226   Best-case results are similar among all three decomposition methods, with slight superior values for

227 EMD and VMD. RBF SVM yielded the best performance, with ACC of 97.5%, 96.7% and 98.2% for

228 EMD, EWT and VMD, respectively. These results are in accordance with the literature, which has

229 accuracy values varying from 90% in [47] to 99,7% in [48]. VMD and autoregression (AR) based

230 quadratic feature extraction with a random forest classifier was used in [29], resulting in up to 96.4%

231 ACC. Random forests with VMD were also used in [28], that combined with semantic feature extraction

232 resulted in a maximum accuracy of 94.1%. Entropy measures in [49] achieved 92.8% and 91.0% ACC.

233 Broader summaries of different methods and respective performance measures are given in [50] and in

234 [36]. The latter uses EMD and similar features of the ones used in this work, achieving 95.7% ACC, 98%

235 SEN and 97% SPEC.

236   The methods presented in this work aim to decompose a signal into AM-FM components, and extract

237 features of each one, which may differentiate "normal" signals from pathologic ones. This has promising

238 applications for the identification of epileptogenic systems and for identifying interictal-ictal state

239 transitions. The feature extraction capabilities can be further explored if each mode was considered as

240 having "well behaved" Hilbert Transforms, which enables the analysis of phase relationships between

241 different modes of the same signal or between different brain regions, if multichannel data is available.

242 Since synchronization is believed to play an important role for ictogenesis, these methods may further

243 assist on unveiling the mechanisms of seizure generation and devising markers to predict transitions to

244 ictal states.

245 Although the results are positive, the application of the presented methods for epileptic seizure

246 detection and classification must face a series of challenges. The Bonn University EEG database is useful

247 for preliminary algorithm evaluation and comparison with similar works. However, considering that the

248 data consists of selected short segments obtained in controlled conditions, it has light requirements in

249 terms of generalization and robustness in comparison with what would be found in a clinical

250 environment. Nevertheless, it is an important evaluation step that should be considered for seizure

251 detection and prediction methods.

252 # Conclusion

253 The development of feature extraction and classification methods is a key step both for understanding

254 of the operating mechanisms of epilepsy, as for clinical analysis, including possible applications for

255 seizure detection and prediction devices.

256 This work has shown that EWT and VMD, relatively new signal decomposition methods, may be

257 used to extract relevant features for classifying and detecting EEG signals of epileptic phenomena.

258 Although EMD and VMD presented the best performance results, the trade-off falls on higher

259 computational power, which may compromise its application for real-time processing. The EWT method,

260 in spite of its slightly worse performance, may be preferable if the context of use that requires faster

261 processing.

262 The use of adaptive decomposition methods is a promising approach due to their ability to separate

263   different AM-FM components that are altered in the presence of seizures (and possibly on periods

264   preceding these events). This would facilitate the extraction of features related to these events, increasing

265   the performance of classification algorithms. However, the extraction of the same features from of non-

266   decomposed signal still results in fairly accurate classifiers. Thus, in contexts with the need of real time

267   processing and limited computational power, the use of these decomposition methods might not be

268   needed for detecting seizures in cases with less strict performance requirements.

269   Another goal of this work was to provide a Python code of these signal decomposition methods for

270   the community. Python is a fast-growing programming language and is currently the third most popular

271   programming language in the world [51] and with widespread applications in neuroscience [52]. The

272   distribution of these packages could further encourage the use of open source programming languages for

273   works involving these specific signal processing methods.

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Conflict of interest

278   None declared.

References

1.   Fiest KM, Sauro KM, Wiebe S, Patten SB, Kwon C-S, Dykeman J, et al. Prevalence and incidence of epilepsy. Neurology. 2017;88: 296–303. doi:10.1212/WNL.0000000000003509

2.   Sander L. The epidemiology of the Epilepsies revisited. Curr Opin Neurol. 2003;16: 165–170. doi:10.1097/01.wco.0000063766.15877.8e

3.   Fisher RS, Acevedo C, Arzimanoglou A, Bogacz A, Cross JH, Elger CE, et al. ILAE Official Report: A practical clinical definition of epilepsy. Epilepsia. 2014;55: 475–482. doi:10.1111/epi.12550

4.   Engel J, Pedley T. Epilepsy - A Comprehensive Textbook. Journal of Chemical Information and Modeling. 1989. doi:10.1017/CBO9781107415324.004

5.   Lopes da Silva FH. The Impact of EEG/MEG Signal Processing and Modeling in the Diagnostic and Management of Epilepsy. IEEE Rev Biomed Eng. 2008;1: 143–156. doi:10.1109/RBME.2008.2008246

6.   Adeli H, Zhou Z, Dadmehr N. Analysis of EEG records in an epileptic patient using wavelet transform. J Neurosci Methods. 2003;123: 69–87. Available: http://www.ncbi.nlm.nih.gov/pubmed/12581851

7.   Acharya UR, Vinitha Sree S, Swapna G, Martis RJ, Suri JS. Automated EEG analysis of epilepsy: A review. Knowledge-Based Syst. Elsevier B.V.; 2013;45: 147–165. doi:10.1016/j.knosys.2013.02.014

8.   Ramgopal S, Thome-Souza S, Jackson M, Kadish NE, Sánchez Fernández I, Klehm J, et al. Seizure detection, seizure prediction, and closed-loop warning systems in epilepsy. Epilepsy Behav. Elsevier B.V.; 2014;37: 291–307. doi:10.1016/j.yebeh.2014.06.023

9.   Mormann F, Andrzejak RG, Elger CE, Lehnertz K. Seizure prediction: the long and winding road. Brain. 2007;130: 314–33. doi:10.1093/brain/awl241

10. Huang NE, Shen Z, Long SR, Wu MC, Shih HH, Zheng Q, et al. The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis. Proc R Soc A Math Phys Eng Sci. 1998;454: 903–995. doi:10.1098/rspa.1998.0193

11. Pachori RB. Discrimination between Ictal and Seizure-Free EEG Signals Using Empirical Mode Decomposition. Res Lett Commun. 2008;2008: 1–5. doi:10.1155/2008/293056

12. Sweeney-Reed CM, Nasuto SJ, Vieira MF, Andrade AO. Empirical Mode Decomposition and its Extensions Applied to EEG Analysis: A Review. Adv Data Sci Adapt Anal. 2018;10: 1840001. doi:10.1142/s2424922x18400016

13. Zahra A, Kanwal N, ur Rehman N, Ehsan S, McDonald-Maier KD. Seizure detection from EEG signals using Multivariate Empirical Mode Decomposition. Comput Biol Med. Elsevier Ltd; 2017;88: 132–141. doi:10.1016/j.compbiomed.2017.07.010

14. Oweis RJ, Abdulhay EW. Seizure classification in EEG signals utilizing Hilbert-Huang transform. Biomed Eng Online. 2011;10: 38. Available: http://www.biomedical-engineering-online.com/content/10/1/38

15. Bajaj V, Pachori R. Classification of Seizure and Non-seizure EEG Signals using Empirical Mode Decomposition. IEEE J Biomed Heal informatics. 2011;16: 1135–1142. doi:10.1109/TITB.2011.2181403

16. Alickovic E, Kevric J, Subasi A. Performance evaluation of empirical mode decomposition, discrete wavelet transform, and wavelet packed decomposition for automated epileptic seizure detection and prediction. Biomed Signal Process Control. Elsevier Ltd; 2018;39: 94–102. doi:10.1016/j.bspc.2017.07.022

17. Li S, Zhou W, Yuan Q, Geng S, Cai D. Feature extraction and recognition of ictal EEG using EMD and SVM. Comput Biol Med. Elsevier; 2013;43: 807–816. doi:10.1016/j.compbiomed.2013.04.002

18. Gilles J. Empirical Wavelet Transform. IEEE Trans Signal Process. 2013;61: 3999–4010. doi:10.1109/TSP.2013.2265222

19. Kumar R, Saini I. Empirical wavelet transform based ECG signal compression. IETE J Res. Taylor & Francis; 2014;60: 423–431. doi:10.1080/03772063.2014.963173

20. Liu W, Cao S, Chen Y. Seismic time-frequency analysis via empirical wavelet transform. IEEE Geosci Remote Sens Lett. IEEE; 2016;13: 28–32. doi:10.1109/LGRS.2015.2493198

21. Bhattacharyya A, Singh L, Pachori RB. Fourier–Bessel series expansion based empirical wavelet transform for analysis of non-stationary signals. Digit Signal Process A Rev J. Elsevier Inc.; 2018;78: 185–196. doi:10.1016/j.dsp.2018.02.020

22. Gabor a J, Leach RR, Dowla FU. Automated seizure detection using a self-organizing neural network. Electroencephalogr Clin Neurophysiol. 1996;99: 257–66. Available: http://www.ncbi.nlm.nih.gov/pubmed/22824647

23. Bahcivan H, Zhang N. Cross-correlation analysis of epileptiform propagation using wavelets. … Med …. 2001; 1804–1807. Available: http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=1020571

24. Chen D, Wan S, Xiang J, Bao FS. A high-performance seizure detection algorithm based on Discrete Wavelet Transform (DWT) and EEG. PLoS One. 2017;12: 1–21. doi:10.1371/journal.pone.0173138

25. Bhattacharyya A, Sharma M, Pachori RB, Sircar P, Acharya UR. A novel approach for automated detection of focal EEG signals using empirical wavelet transform. Neural Comput Appl. Springer London; 2018;29: 47–57. doi:10.1007/s00521-016-2646-4

26. Saxena S, Hemanth C, Sangeetha RG. Classification of normal, seizure and seizure-free EEG signals using EMD and EWT. 2017 International Conference on Nextgen Electronic Technologies: Silicon to Software (ICNETS2). IEEE; 2017. pp. 360–366. doi:10.1109/ICNETS2.2017.8067961

27. Dragomiretskiy K, Zosso D. Variational Mode Decomposition. IEEE Trans Signal Process. 2014;62: 531–544. doi:10.1109/TSP.2013.2288675

28. Ravi Kumar M, Srinivasa Rao Y. Epileptic seizures classification in EEG signal based on semantic features and variational mode decomposition. Cluster Computing. Springer US; 2018: 1–11. doi:10.1007/s10586-018-1995-4

29. Zhang T, Chen W, Li M. AR based quadratic feature extraction in the VMD domain for the automated seizure

detection of EEG using random forest classifier. Biomed Signal Process Control. Elsevier Ltd; 2017;31: 550–559. doi:10.1016/j.bspc.2016.10.001

30. Taran S, Bajaj V. Clustering Variational Mode Decomposition for Identification of Focal EEG Signals. IEEE Sensors Lett. 2018;2: 1–4. doi:10.1109/LSENS.2018.2872415

31. Andrzejak R, Lehnertz K, Mormann F, Rieke C, David P, Elger C. Indications of nonlinear deterministic and finite-dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Phys Rev E. 2001;64: 061907. doi:10.1103/PhysRevE.64.061907

32. Laszuk D. Python implementation of Empirical Mode Decomposition algorithm [Internet]. 2017. Available: https://laszukdawid.com/codes/

33. Daubechies I. Ten Lectures on Wavelets [Internet]. Society for Industrial and Applied Mathematics; 1992. doi:10.1137/1.9781611970104

34. Gilles J. Empirical Wavelet Transforms [Internet]. Available: https://www.mathworks.com/matlabcentral/fileexchange/42141-empirical-wavelet-transforms

35. Zosso D. Variational Mode Decomposition Toolbox [Internet]. 2013. Available: https://www.mathworks.com/matlabcentral/fileexchange/44765-variational-mode-decomposition

36. Martis RJ, Acharya UR, Tan JH, Petznick A, Yanti R, Chua CK, et al. Application of empirical mode decomposition (emd) for automated detection of epilepsy using EEG signals. Int J Neural Syst. 2012;22: 1250027. doi:10.1142/S012906571250027X

37. Welch P. The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short, modified periodograms. IEEE Trans Audio Electroacoust. 1967;15: 70–73. doi:10.1109/TAU.1967.1161901

38. Cohen L, Lee C. Instantaneous bandwidth for signals and spectrogram. Int Conf Acoust Speech, Signal Process. IEEE; 1990; 2451–2454. doi:10.1109/ICASSP.1990.116086

39. Hjorth B. EEG analysis based on time domain properties. Electroencephalogr Clin Neurophysiol. 1970;29: 306–10. Available: http://www.ncbi.nlm.nih.gov/pubmed/4195653

40. Navascués MA, Sebastián M V. Time domain indices and discrete power spectrum in electroencephalographic processing. Int J Comput Math. 2009;86: 1968–1978. doi:10.1080/00207160903023599

41. Pedregosa F, Varoquaux G, Gramfort A, Michel V, Thirion B, Grisel O, et al. Scikit-learn: Machine Learning in Python. J Mach Learn Res. 2012;12: 2825–2830. doi:https://dl.acm.org/citation.cfm?id=2078195

42. Guyon I, Weston J, Barnhill S, Vapnik V. Gene Selection for Cancer Classification using Support Vector Machines. Mach Learn. 2002;46: 389–422. doi:10.1023/A:1012487302797

43. Altman NS. An Introduction to Kernel and Nearest-Neighbor Nonparametric Regression. Am Stat. 1992;46: 175–185. doi:10.1080/00031305.1992.10475879

44. Cortes C, Vapnik V. Support-vector networks. Mach Learn. 1995;20: 273–297. doi:10.1007/BF00994018

45. Rasmussen CE, Williams CKI. Gaussian Processes for Machine Learning. Cambridge, Massachusetts: The MIT Press; 2006. doi:10.1142/S0129065704001899

46. Hinton GE. Connectionist learning procedures. Artif Intell. 1989;40: 185–234. doi:10.1016/0004-3702(89)90049-0

47. Hsu KC, Yu SN. Detection of seizures in EEG using subband nonlinear parameters and genetic algorithm. Comput Biol Med. 2010;40: 823–830. doi:10.1016/j.compbiomed.2010.08.005

48. Acharya UR, Sree SV, Alvin APC, Yanti R, Suri JS. Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals. Int J Neural Syst. 2012;22: 1250002. doi:10.1142/S0129065712500025

49. Li P, Karmakar C, Yearwood J, Venkatesh S, Palaniswami M, Liu C. Detection of epileptic seizure based on entropy analysis of short-term EEG. PLoS One. 2018;13: 1–17. doi:10.1371/journal.pone.0193691

50. Acharya UR, Oh SL, Hagiwara Y, Tan JH, Adeli H. Deep convolutional neural network for the automated detection and diagnosis of seizure using EEG signals. Comput Biol Med. Elsevier Ltd; 2018;100: 270–278. doi:10.1016/j.compbiomed.2017.09.017

51. The state of the octoverse [Internet]. 2018. Available: https://octoverse.github.com/

52. Muller E, Bednar JA, Diesmann M, Gewaltig M-O, Hines M, Davison AP. Python in neuroscience. Front Neuroinform. 2015;9: 14–17. doi:10.3389/fninf.2015.00011

Fig S1. Decomposition of inter-ictal EEG. (A) Original non-decomposed signal. (B) First six extracted IMFs with EMD. (C) 6 components extracted with EWT. (D) 5 components extracted with VMD.

Fig S2. Decomposition of normal EEG. (A) Original non-decomposed signal. (B) First six extracted IMFs with EMD. (C) 6 components extracted with EWT. (D) 5 components extracted with VMD.