35th Annual International Conference of the IEEE EMBS
Osaka, Japan, 3 - 7 July, 2013

EEG Seizure Detection and Epilepsy Diagnosis using a Novel Variation of Empirical Mode Decomposition

M. Kaleem, A. Guergachi, S. Krishnan

***Abstract*— Epileptic seizure detection and epilepsy diagnosis based on feature extraction and classification using electroencephalography (EEG) signals is an important area of research. In this paper, we present a simple and effective approach based on signal decomposition, using a novel variation of the Empirical Mode Decomposition called Empirical Mode Decomposition-Modified Peak Selection (EMD-MPS). EMD-MPS allows time-scale based de-trending of signals, allowing signals to be separated directly into a de-trended component, and a trend, according to a frequency separation criterion. Features are extracted from the decomposed components, and a simple classifier, namely the 1-NN classifier is used for three classification tasks. The technique is tested on a publicly available EEG database, and a classification accuracy of 99% for epilepsy diagnosis task, and 100% and 98.2% for two seizure detection tasks is obtained. These results are better than, or comparable to previous results using the same EEG database, but have been obtained with a simpler and computationally fast signal analysis and classification method.**

I. INTRODUCTION

Epilepsy is a neurological disorder affecting a very large number of people worldwide [1]. There is considerable research concerned with computer-based methods for seizure detection and epilepsy diagnosis using electroencephalography (EEG) signals [2] . Given the non-linear and non-stationary nature of EEG signals, signal processing methods for non-stationary signal analysis, such as empirical mode decomposition (EMD), time-frequency analysis, and wavelets, have been frequently used for automated seizure detection using EEG signals, e.g. [1][2][3][4]. The adaptive nature of EMD-based decomposition methods makes them particularly suitable for non-linear signal analysis [5].

We previously proposed a novel modification to the EMD algorithm named empirical mode decomposition-modified peak selection (EMD-MPS) [6]. In the EMD-MPS method, the sifting process of EMD [7] is modified to use intelligent peak selection in short-time windows of length τ. Based on different values of τ, different decompositions of a signal into what we term as τ-functions are possible. Therefore the short-time window acts as an operator which allows separation of different frequency components in a signal into τ-functions, as determined by the length τ of the short-time window. We have previously established a relation between the frequency components decomposed and the value of τ, and have shown that using an appropriate selection of values of τ allows a novel time-scale based de-trending of signals [6].

In this paper, we present a novel method based on the EMD-MPS method for epilepsy diagnosis and seizure detection using EEG signals. The first part of our methodology consists of using EMD-MPS to decompose EEG signals into a de-trended component, and a trend, using a frequency separation criterion. Features are then extracted from the two decomposed components, which form feature vectors used for classification using a simple classifier, namely the 1-NN classifier. The next sections will provide more details of the proposed method.

II. EMPIRICAL MODE DECOMPOSITION-MODIFIED PEAK SELECTION

EMD-MPS uses the sifting process to decompose a signal. However, a criterion for choosing the extrema based on short-time windows of length τ is used. Let us define an operator $W_i^\tau(\cdot),\ i = 1...k, i \in \mathbb{Z},\ 0 < \tau < L, L \in \mathbb{R}$, which, given a signal $x[n]$ of length L, produces the i-th τ-function T_i, such that $\mathrm{T}_i[n] = W_i^\tau(x[n])$, as given in Algorithm 1.

Algorithm 1 EMD-MPS Algorithm

1: Choose a short-time window τ.
2: For each interval τ over the whole signal length, identify the highest/lowest from among the maxima/minima within τ.
3: Find the upper and lower envelopes $E_{n(U)}$ and $E_{n(L)}$ by interpolating all maxima/minima identified (one maxima and minima each per τ).
4: Calculate the local mean of the upper and lower envelopes $E_{n(mean)} = \frac{E_{n(U)}+E_{n(L)}}{2}$.
5: Update $x[n]$ by subtracting the mean from it $x[n] \leftarrow x[n] - E_{n(mean)}$. Continue the previous steps till a stopping criterion is met, at which point $x[n]$ is reduced to a τ-function T_1.
6: Subtract T_1 from $x[n]$ to get a residue $r[n]$.
7: Take $r[n]$ as the starting point instead of $x[n]$, and repeat the previous steps of the algoritm till all τ-functions T_i in the signal are found.

The coarse-grained τ-functions may contain different co-existing modes of oscillation, each superimposed on the other, due to the short-time window τ setting an upper limit on the periods of the oscillations that can be included in any given τ-function obtained using the EMD-MPS method. This limit is determined by :

$$F = \frac{F_s}{\tau} \tag{1}$$

M. Kaleem (corresponding author) and S. Krishnan are with the department of Electrical Engineering, Ryerson University, Toronto, Canada. m2kaleem@ryerson.ca

A. Guergachi is with the Ted Rogers School of Information Technology Management, Ryerson University, Canada.

where F_s represents the sampling frequency.

As an example for this relation, a value of τ=25 (in samples) corresponds to a frequency value F=40 samples/second for F_s=1000 samples/second. Using this value of τ, only one peak (maxima and minima each) in each 25 sample interval will be used in the envelope formation, and the sifting process should then decompose all $F \leq 40$ samples/second oscillatory components, and let all components with $F > 40$ samples/second pass through un-decomposed in one τ-function. Due to the non-linear nature of decomposition and mode-mixing phenomenon [7], the frequency separation does not represent a sharp cut-off. Additionally, in practice the value of τ is qualified by a scaling constant k, such that $\hat{\tau} = k\tau$, and $0 < k \leq 1$. The relation in Eq. 1 and the scaling constant k have been empirically validated using fractional Gaussian noise in our previous works [6].

III. Method

The next subsections will present different aspects of the proposed methodology for EEG signal classification in the context of epilepsy diagnosis and seizure detection.

A. Data

The EEG signals used in this paper come from the data made public by the University of Bonn [8]. The data consists of EEG signals in five sets named A, B, C, D and E. Signals in sets A and B are from epilepsy free volunteers, whereas signals in sets C, D and E come from epilepsy patients. The signals in sets C and D have been recorded during epilepsy-free intervals, with set E containing only seizure signals. In each set there are 100 scalp EEG signals of 23.6 seconds duration sampled at 173.61 Hz, with each signal having 4097 samples, and a spectral bandwidth ranging from 0.5 Hz to 85 Hz. This data has been used in numerous previous studies (e.g. [2][3][4][9]), but in general many of the previous studies have tested classification only between sets A and E, and between sets ABCD and E. For this paper, we apply our methodology to test binary classification in the following three scenarios:

1) Classification between sets A and E. This is the most commonly used scenario in previous works, and has bee used to test the efficacy of proposed methodologies for seizure detection.
2) Classification between sets AB and CD. This is used to test performance of the method in classifying signals mixed with different observational conditions or recordings at different spatial locations. Also, this scenario is relevant for the case of epilepsy diagnosis, as sets AB contain normal signals, and sets CD epileptic signals.
3) Classification between sets ABCD and E. This is relevant in terms of a seizure detection scenario, and also has relevance for clinical applications [3].

B. Decomposition using EMD-MPS

EMD-MPS is used for a time-scale based de-trending of EEG signals, such that each EEG signal is decomposed into one τ-function T_1 representing the de-trended signal containing the higher frequency components, and another τ-function T_2 representing the trend of the signal. This is done by appropriate selection of a value of τ according to Eq. 1, and does not require estimation of a trend model for model-based de-trending, or knowledge of the statistical properties of IMFs, as is the case for EMD-based de-trending approaches proposed in literature, e.g. [10]. Further, EMD-MPS decomposition into two τ-functions is computationally faster compared to EMD decomposition into at most $\log_2(N)$ IMFs [7], where N is the length of the signals, followed by partial reconstruction of IMFs back into a de-trended component and the trend [10].

A value of τ for decomposition of EEG signals using EMD-MPS was found as follows. First, a frequency separation value of F=8 Hz was chosen, such that T_1 contains frequency components with frequency values greater than 8 Hz, and T_2 represents the trend containing frequencies lower than 8 Hz. Due to space limitations, the details of choice of F=8 Hz are not provided here, but it was objectively selected based on the highest classification accuracy obtained compared to other values of frequency separation evaluated.

Using Eq. 1 and the signals' sampling frequency value of F_s=173.16 Hz, the value of τ obtained for F=8 Hz is given by τ=21.6. However, for decomposition, we have to use the value $\hat{\tau}$, which is τ scaled by a constant k as described in Section II. A good estimate for the value of k is given by $k \approx 0.44$ [6], such that τ=21.6 corresponds to value of $\hat{\tau}$=9.5. Therefore, all EEG signals were decomposed using $\hat{\tau}$=9.5. In this regard, Fig. 1 shows an example EEG signal from set C, and the τ-functions T_1 and T_2 obtained with a value of $\hat{\tau}$=9.5.

C. Extraction of Features and Classification

After decomposition of the EEG signals into two τ-functions each, a total of four features are extracted. One feature is extracted from the τ-functions, and the remaining three from the frequency-domain representation of the τ-functions obtained using the discrete Fourier transform (DFT). Computationally fast implementations of the DFT algorithm are available in different software packages, hence our approach is expected to be computationally more efficient than time-frequency and wavelet decomposition based approaches, e.g. [2][4].

The discrete Fourier transform (DFT) of both τ-functions T_i results in a complex-valued function $\hat{\mathbf{F}}_i$. The real-valued single-sided amplitude spectrum of the τ-functions, given by $\hat{f}_i$, is then obtained by taking the absolute value of $\hat{\mathbf{F}}_i$. Three features are subsequently extracted from $\hat{f}_i$.

The four extracted features are listed below:

1) The energy E_i of the τ-functions T_i, given by:

$$E_i = \sum_{n=1}^{N} \mathrm{T}_i^2[n], \ i = 1, 2 \tag{2}$$

where N is the length of T_i.

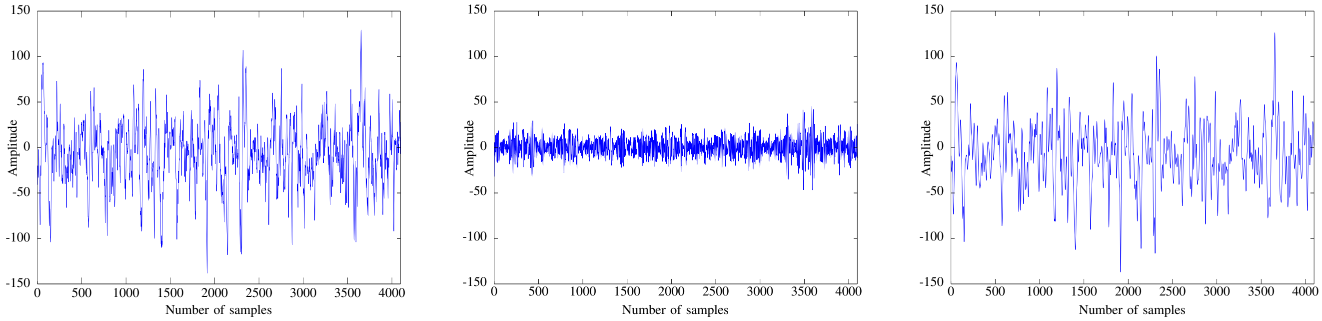

Fig. 1. (Left) EEG signal from an epilepsy patient (from set C). (Middle) τ-function T_1, representing de-trended signal. (Right) τ-function T_2, representing the trend. These τ-functions have been obtained using a value of τ=21.6 ($\hat{\tau}$=9.5) corresponding to a frequency separation value F=8 Hz.

2) The sum of the amplitude spectrum, $S_{\hat{f}_i}$, calculated as:

$$S_{\hat{f}_i} = \sum_{n=1}^{M} \hat{f}_i[n], \; i = 1,2 \tag{3}$$

3) The sparsity of the amplitude spectrum, $SP_{\hat{f}_i}$, calculated as:

$$SP_{\hat{f}_i} = \frac{\sqrt{M} - (\sum_{n=1}^{M} \hat{f}_i[n]) / \sqrt{\sum_{n=1}^{M} \hat{f}_i^2[n]}}{\sqrt{M} - 1}, \; i = 1,2 \tag{4}$$

4) The sum of derivative of the amplitude spectrum, $D_{\hat{f}_i}$, calculated as:

$$D_{\hat{f}_i} = \sum_{n=1}^{M-1} \hat{\hat{f}}_i[n]^2, \; i = 1,2 \tag{5}$$

where $\hat{\hat{f}}_i[n] = \hat{f}_i[n+1] - \hat{f}_i[n]$, for $n = 1, ..., M-1$, and M is the length of $\hat{f}_i$.

We have previously used features $SP_{\hat{f}_i}$ and $D_{\hat{f}_i}$ for pathological speech classification [11], achieving a high classification accuracy. EEG signals from healthy subjects are expected to have higher values for the sparsity feature $SP_{\hat{f}_i}$ compared to values from epileptic patients. This is due to $SP_{\hat{f}_i}$ distinguishing the non-frequently occurring transient components in epileptic signals from the normally occurring frequency components in non-epileptic signals. However, in order to reduce the number of feature vectors, we extract this feature only from τ-function T_2, which represents the low frequency trend of the EEG signals. This way, any abnormal activity occurring in the lower frequency range contained in the trend will be captured as a discriminative feature.

Similarly, the feature $D_{\hat{f}_i}$ is a good measure of abrupt changes and discontinuities in the signal representation in the frequency domain, which are expected to occur more frequently in epileptic signals. This feature is extracted from the τ-function T_1, which represents the de-trended part of the signals, and contains higher frequency components, where abrupt changes and discontinuities are more likely.

IV. Results

The four features described in the previous section were used to form feature vectors in order to test classification between the sets in the three scenarios. In order to keep the overall methodology simple, a 1-NN classifier was chosen, and classification results estimated using the ten-fold cross validation method. The classification results thus obtained for the three scenarios are shown in Table I, and discussed in the next sections.

A. Classification between sets A and E

The classification accuracy obtained for classification between sets A and E was 100%, thereby matching the results in recent works [2][3], and improving on previous results (e.g. as listed in [2]). Importantly, however, the 100% classification accuracy in our work has been obtained using just a single feature, namely $S_{\hat{f}_i}$, the sum of the amplitude spectrum. This demonstrates the efficacy and simplicity of our approach, as well as the utility of approaches based on adaptive signal decomposition.

B. Classification between sets AB and CD

The classification between EEG signals from healthy subjects (sets AB) and epileptic patients (sets CD) is relevant in terms of epilepsy diagnosis, and a 99% classification accuracy is obtained for this case using all four features. This is comparable to the 100% classification accuracy presented in [2], which is one work where this classification case is considered, using wavelet variances as features in conjunction with a 1-NN classifier.

Furthermore, it was found that removing the feature vector of feature E_i obtained from τ-function T_2 did not affect the classification accuracy. Hence only 5 feature vectors were used to obtain the classification accuracy of 99%. Also, to check the effectiveness of the extracted features in discriminating between EEG signals from sets AB and CD, we performed un-paired *t*-tests of the null hypothesis that the feature values obtained from the τ-functions extracted from signals of both sets have the same mean. The p-values thus obtained for the five feature vectors used for classification confirmed rejection of the null hypothesis for all cases. In this regard, the boxplot in Fig. 2 shows distribution of values for the used features, and also shows the p-values obtained by the un-paired *t*-tests. It can be concluded that the combination of all used features determines the effectiveness

TABLE I

CLASSIFICATION ACCURACY FOR THE 3 SCENARIOS (SECTION III-A) USING 1-NN CLASSIFIER AND 10-FOLD CROSS-VALIDATION

Sets:	A & E	AB & CD	ABCD & E
Classification Accuracy:	100%	99%	98.2%

in discrimination between signals from healthy subjects and epileptic patients.

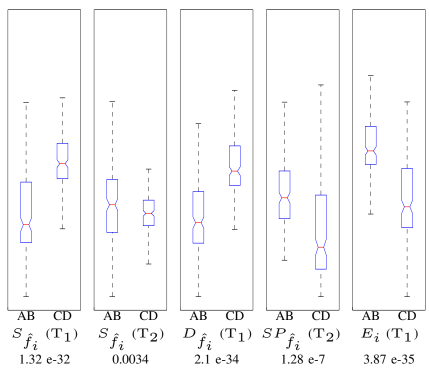

Fig. 2. Boxplots showing the distribution of values of features from the signal sets AB and CD. These features have been extracted from τ-functions as shown in the figure. The difference in the distribution of feature values obtained from signals in both sets was confirmed using un-paired t-tests, with the resulting p-values also shown. (Note: e-x means $\times 10^x$)

C. Classification between sets ABCD and E

Classification between sets ABCD and E represents the case of seizure detection. For this scenario, and using the same five feature vectors as described in Section IV-B, a classification accuracy of 98.2% was obtained. This result improves on the classification accuracy of 97.73% presented in [4], and is comparable to the classification accuracy of 98.27% presented in [3]. Both of these results, however, have been obtained with more involved signal analysis methods used with complicated classifiers, namely time-frequency analysis with feed-forward artificial neural network in the case of former, and multi-wavelet transform and entropy feature with multi-layer perceptron neural network (MLPNN) for the latter. Our result is also comparable to the classification accuracy of 100% presented in [2], which has been obtained with wavelet variance features extracted after wavelet decomposition of the signals and using a 1-NN classifier. In comparison with the methodology of [2], our signal analysis method is computationally more simple and adaptive, as the decomposition does not require finding an appropriate basis.

V. CONCLUSIONS

This paper presented a novel method of EEG signal analysis that can be used for epilepsy diagnosis and seizure detection using a simple classification scheme. The signal analysis method is based on a novel decomposition scheme, which is characterized by its computational simplicity and adaptivity. Features are extracted from the decomposed components of the signal, and a 1-NN classifier is used to obtain high classification accuracy for different classification tasks. The classification results obtained are better than or comparable to other approaches using more involved signal analysis methods and complicated classifiers. A very important advantage of our method is the flexibility of decomposition and feature extraction, since decomposition is based on a frequency separation criterion, and different features may be extracted from the τ-functions. This allows the method to be ported to a different set of biomedical signals in a different domain, as we have demonstrated in the context of mental task classification using EEG signals [12]. Further extensions of this work include application to other EEG data sets, and evaluation of different feature sets to further improve the classification accuracy.

REFERENCES

[1] L. Orosco, E. Laciar, A.G. Correa, A. Torres, and J.P. Graffigna, "An Epileptic Seizures Detection Algorithm based on the Empirical Mode Decomposition of EEG", *31st Annual International Conference of the IEEE EMBS*, Minneapolis, Minnesota, USA, September 2-6, 2009, pp. 2651-2654.

[2] S. Xie and S. Krishnan, "Wavelet-based sparse functional linear model with applications to EEGs seizure detection and epilepsy diagnosis", *Medical & Biological Engineering & Computing*, doi:10.1007/s11517-012-0967-8, 2012, pp. 1-12.

[3] L. Guo, D. Rivero and A. Pazos, "Epileptic seizure detection using multiwavelet transform based approximate entropy and artificial neural networks", *Journal of Neuroscience Methods*, 193 (2010), 156-163.

[4] A.T. Tzallas, M.G. Tsipouras and D.I. Fotiadis, "Automatic Seizure Detection Based on Time-Frequency Analysis and Artificial Neural Networks", *Computational Intelligence and Neuroscience*, 2007, 13 pages.

[5] C. Park, D. Looney, P. Kidmose, M. Ungstrup and D.P. Mandic, "Time-Frequency Analysis of EEG Asymmetry Using Bivariate Empirical Mode Decomposition", *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, Vol. 19, Issue 4, 2011, pp. 366-373.

[6] M.F. Kaleem, A. Guergachi and S. Krishnan, "A Variation of Empirical Mode Decomposition with Intelligent Peak Selection in Short Time Windows", *Accepted for publication in Proceedings of 38th International Conference on Acoustics, Speech, and Signal Processing (ICASSP)*, Vancouver, Canada, 2013.

[7] N. E. Huang, Z. Shen, S. R. Long, M. C. Wu, H. H. Shih, Q. Zheng, N. C. Yen, C. C. Tung and H. H. Liu, The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis, *Proceedings of the Royal Society of London. Series A: Mathematical, Physical and Engineering Sciences*, Vol. 454, Issue. 1971, March 1998, pp. 903-995.

[8] R.G. Andrzejak, K. Lehnertz, C. Rieke, F. Mormann, P. David and C.E. Elger, "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, 64, 061907*, 2001.

[9] H. Adeli, S. Ghosh-Dastidar and N. Dadmehr, "A Wavelet-Chaos Methodology for Analysis of EEGs and EEG Subbands to Detect Seizure and Epilepsy", *IEEE Transactions on Biomedical Engineering*, Vol. 54, Issue. 2, 2007, pp. 205-211.

[10] A. Moghtaderi, P. Borgnat and P. Flandrin, "Trend Extraction for Seasonal Time Series Using Ensemble Empirical Mode Decomposition", *Advances in Adaptive Data Analysis*, Vol. 3, Issue. 1 & 2, 2011, pp. 41-61.

[11] B. Ghoraani and S. Krishnan, "A Joint Time-Frequency and Matrix Decomposition Feature Extraction Methodology for Pathological Voice Classification", *EURASIP Journal on Advances in Signal Processing*, 2009, 11 pages.

[12] M. Kaleem, A. Guergachi and S. Krishnan, "Application of a Variation of Empirical Mode Decomposition and Teager Energy Operator to EEG Signals for Mental Task Classification", *Accepted for publication in Proceedings of 35th Annual International Conference of the IEEE EMBS*, Osaka, Japan, 2013.