LUMEN ET VIRTUS

Automatic detection of generalized epilepsy through multivariate singular spectral analysis

https://doi.org/10.56238/levv15n39-016

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ABSTRACT
The collection and interpretation of electroencephalogram (EEG) signals are laborious and time-consuming activities, requiring a trained specialist to perform them. Automatic detection of epilepsy may be a solution. However, research on the subject has focused on detecting specific, non-generalized epilepsies in a larger patient population. Decomposition of signals, through singular spectrum analysis, of records of patients with epilepsy for subsequent verification of the energy limit. These records were available in a publicly accessible signal bank. The use of different weights to calculate means and standard deviations of the energy series and different sample sizes contributed to improve the diagnosis.

Keywords: Epilepsy, Generalized Automatic Detection, Multivariate Singular Spectral Analysis.

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INTRODUCTION

Classified as a neurological disorder that affects the brain, epilepsy affects about 50 million people worldwide, leading to reduced productivity and imposing restrictions on daily life (BERGIL; YILDIZ, 2016). Its diagnosis given by neurophysiologists is based on the visual analysis of the rhythmic fluctuations of the brain described by the electroencephalogram (EEG).

It turns out that, as described in Bajaj and Pachori (2013) and Scolaro (2014), diagnosing abnormal EEG patterns through visual analysis is a laborious and time-consuming activity. This is because it requires the reading of up to 21 channels that are viewed on 10-second screens. In addition to being laborious and time-consuming, it can also, due to subjectivity, present different analyses when performed by experienced neurophysiologists (SCOLARO, 2014).

In order to reduce the workload, some techniques (OROSCO et al., 2009; BAJAJ; PACHORI, 2013; SCOLARO, 2014; BERGIL; YILDIZ, 2016) on automatic detection of abnormal patterns in EEG are proposed in studies on the subject. Through different methodologies, they make use of signal decomposition models, which treat the rhythmic fluctuations of the brain, from which the trend, harmonic and noise components are extracted. Then, classifiers of the characteristics of these components identify the patterns. The importance of these models is seen in the description of the application of discrete wavelet transform (TDW), singular value decomposition (DVS), empirical mode decomposition (DME) in addition to principal component analysis (PCA) (ALOTAIBY et al., 2014).

There is no doubt about the contribution of signal decomposition models to the automatic detection of abnormal EEG patterns, however, the use of singular spectral analysis (AES) in investigations (SHAHID et al., 2013; PARVEZ; PAUL, 2014; THANARAJ; CHITRA, 2014) for the detection of abnormal EEG patterns, whose epilepsies are classified as generalized, did not present the best performances when compared to the use of DME and TDW models (OROSCO et al., 2009; BAJAJ; PACHORI, 2013; BERGIL; YILDIZ, 2016).

Based on searches carried out in national and international journals, no investigations were found on the identification of abnormal EEG patterns, whose epilepsies are classified as generalized, through the multivariate singular spectral analysis (AESM) model.

Although the characteristics of the signals through the AES are extracted, corresponding to the underlying physiological phenomena, when considering the multivariate analysis, the common harmonics are identified, ensuring more consistent information on the frequency (SANEI; HASSANI, 2016). Thus, it is expected that through its use, abnormal patterns in the EEG of epilepsies classified as generalized will be identified, useful to the automatic detection process, through the manifestations of greater variability of the signs.

Therefore, in order to contribute to investigations on the identification of abnormal patterns in the EEG whose epilepsies are classified as generalized, the multivariate singular spectral analysis model is applied to the EEG recordings and, then, the minimum duration energy limit is calculated in order to improve the performance of the identification of these patterns.

MULTIVARIATE SINGULAR SPECTRAL ANALYSIS

The first investigations on the AESM model were made with climate-related data and represented by nearby localities or regions on a map (KEPPENNE; GHIL, 1993; PLAUT; VAUTARD, 1994). Then, the work carried out was applied to economic data, such as Patterson et al. (2011), as well as to the production of different industrial segments, according to Hassani and Mahmoudvand (2013) in addition to Pinheiro and Senna (2015).

In its presentation, the multivariate analysis model consists of the complementary stages: decomposition and reconstruction (HASSANI; MAHMOUDVAND, 2013). The first complementary stage is formed by the embedding and DVS steps, and the reconstruction stage is given by the grouping step, responsible for grouping the signal components excluding noise, in addition to the average diagonal step.

The embedding step can be considered as a mapping that transfers a set M of signals, with length N or quantity of observations in the period investigated, one-dimensional $Y^{(i)} = y_1^{(i)},\dots, y_N^{(i)}$, to a multidimensional matrix $\left[X_1^{(i)},\dots, X_K^{(i)}\right]$. Its vectors $x_j^{(i)} = \left(y_j^{(i)},\dots, y_{j+L}^{(i)}\right)^T \in R^{L_i}$, where $i = 1,\dots,M$, with L corresponding to the length of the window and $K = N - L + 1$ the number of columns of the matrix trajectory $X^{(i)}$. Vectors $x_j^{(i)}$ are called lagged vectors.

By using a set M of signs, as described in Hassani and Mahmoudvand (2013), the length of the window L can be an integer $L = N + 1/(M+1)$. The result of the embedding step is the formation of the block of matrix trajectories X_V, as follows:

$$X_V = \begin{bmatrix} X^{(1)} \\ \vdots \\ X^{(M)} \end{bmatrix} \qquad (01)$$

The path matrix block X_V represents a vertical format, that is, the trajectory matrices are arranged vertically, one below the other. In the literature they are also arranged horizontally or side by side, however, for Hassani and Mahmoudvand (2013) the vertical format better considers the effect of cross-correlation and orthogonality issues, and is therefore applied in this investigation.

In DVS para $X_V X_V^T$ is denoted by $\lambda_{V_1},..., \lambda_{V_{M\times L}}$ the eigenvalues of $X_V X_V^T$ in decreasing order of magnitude $\left(\lambda_{V_1} \geq ... \geq \lambda_{V_{M\times L}} \geq 0\right)$ and by $U_{V_1},..., U_{V_{M\times L}}$ the orthogonal eigenvectors. The matrix $X_V X_V^T$, of dimension $(ML \times ML)$, is given as follows:

$$X_V X_V^T = \begin{bmatrix} X^{(1)}X^{(1)T} & X^{(1)}X^{(2)T} & \cdots & X^{(1)}X^{(M)T} \\ X^{(2)}X^{(1)T} & X^{(2)}X^{(2)T} & \cdots & X^{(2)}X^{(M)T} \\ \vdots & \vdots & \ddots & \vdots \\ X^{(M)}X^{(1)T} & X^{(M)}X^{(2)T} & \cdots & X^{(M)}X^{(M)T} \end{bmatrix} \tag{02}$$

Whereas: $E_{V_i} = \sqrt{\lambda_{V_i}} U_{V_i} V_{V_i}^T$

$$X_V = E_{V_1} + ... + E_{V_D} \tag{03}$$

where $E_{V_i} = \sqrt{\lambda_{V_i}} U_{V_i} V_{V_i}^T$ represents a block of elementary matrices, $V_{V_i} = X_V^T U_{V_i} \Big/ \sqrt{\lambda_{V_i}}$, the set $\sqrt{\lambda_{V_i}}, U_{V_i}, V_{Vi}$ as eitriple, and $D = \max\{i \mid \lambda_{V_i} > 0\}$, that is, the number of nonzero eigenvalues $X_V X_V^T$.

The grouping step corresponds to dividing the matrices of the elementary matrix blocks $E_{V_1},...,E_{V_D}$ into disjoint groups by summing them within each group. The unfolding of the set of indices $J = \{1,...,D\}$ into disjoint subsets $I_1,...,I_m$ corresponds to the representation:

$$X_V = E_{V I_1} + ... + E_{V I_m} \tag{04}$$

com $E_{V I_1},...,E_{V I_m}$ defined as blocks of resulting arrays.

As a simple case, for the frequency domain, which presents the components of the signal, two groups of indices are used, according to $I_1 = \{1,...,a\}$ and $I_2 = \{a+1,...,D\}$, the first group associated with trend and harmonic and the second with noise, with a an integer greater than 1. Thus, the matrices of the resulting matrix block must be further converted to a vector $\tilde{y}_N^{(i)}$ by means of the diagonal mean step.

If we consider the one-dimensional sign $Y^{(i)} = \left[y_1^{(i)},..., y_N^{(i)} \right]^T$, the same will be given by:

$$X^{(i)} = \begin{bmatrix} y_{1,1}^{(i)} & y_{1,2}^{(i)} & y_{1,3}^{(i)} & \cdots & y_{1,K}^{(i)} \\ y_{2,1}^{(i)} & y_{2,2}^{(i)} & y_{2,3}^{(i)} & \cdots & y_{2,K}^{(i)} \\ y_{3,1}^{(i)} & y_{3,2}^{(i)} & y_{3,3}^{(i)} & \cdots & y_{3,K}^{(i)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ y_{L,1}^{(i)} & y_{L,2}^{(i)} & y_{L,3}^{(i)} & \cdots & y_{L,K}^{(i)} \end{bmatrix} \qquad (05)$$

com $y_{1,1}^{(i)}$ representing the first observation of sign (i) arranged in the first row and column and $y_{L,1}^{(i)}$ observation L of sign (i) arranged in row L and first column. Still in the same matrix $y_{1,2}^{(i)}$ that indicates occupying the first row and second column is the second observation of sign (i), also arranged in $y_{2,1}^{(i)}$ since the observations are presented in a lagged way. Thus, the diagonal average will be obtained as:

$$\tilde{x}^{(i)} = \begin{bmatrix} y_{1,1}^{(i)} \\ \dfrac{y_{1,2}^{(i)} + y_{2,1}^{(i)}}{2} \\ \dfrac{y_{1,3}^{(i)} + y_{2,2}^{(i)} + y_{3,1}^{(i)}}{3} \\ \vdots \\ \vdots \\ y_{L,K}^{(i)} \end{bmatrix} \qquad (06)$$

More information about the model can be seen in Hassani and Mahmoudvand (2013).

MATERIALS AND METHOD

The dataset used in this study was extracted from 171 files with a total of 181 epileptic events. These events were identified by experienced neurophysiologists and available in the Institute for Signal and Information Processing (ISIP) database.

The signals were used with a *butterworth* filter with a bandwidth of 0.5 to 25 Hz, as this is the pathological frequency range (RUNARSSON; SIGURDSSON, 2005; PARREIRA, 2006; YOO et al. 2013; SCOLARO, 2014). The application of the filter is defined in the literature as pre-processing. Then, the pre-processed signals (sampling at 256 Hz) were decomposed using the AESM model.

The proposed methodology is given in three stages: preliminary adjustment, training and testing.

For the purposes of the investigation, the multivariate decomposition of the signals was obtained by calculating the elemental matrices for each channel. After preliminary adjustment, it was concluded that the first 10 elementary matrices (converted into 10 subsignals through the diagonal mean) contributed to the detection of abnormal EEG patterns, and were thus used. This is due to the fact that the first matrices can explain the greater variability of the signal (GOLYANDIN; KOROBEYNIKOVA, 2013).

Considering that $\tilde{y}_N^{(i)}$ it represents a sub-signal obtained from the elemental matrix, each of them will be used for the calculation of energy, as follows:

$$E_{seg_j} = \frac{1}{H}\sqrt{\sum_{H/2-f+(j-1)*H-(j-1)*2}^{f+H/2-1} (\tilde{y}_N^{(i)})^2} \qquad (07)$$

with seg the segment number being an integer given in the interval $j = 1, 2, \ldots, sr \times ti/(H/2) - 1$, sr the sampling rate, ti the time interval used in seconds, H the extent in samples of the moving overlapping window for the energy calculation, and f given by $((H/2)-1)*j$.

For illustrative purposes, considering ti equal to 10 seconds or 2560 samples, 101 segments are formed. The first segment defined by samples 1 to 50, the second segment from 26 to 75 and so on to define the energy at (07) for each of the 101 segments.

In the investigation H, it corresponds to 20.3125% of the sampling at 256 Hz, with the intention of capturing the effects of abnormal EEG patterns (sharp waves and spikes), since these patterns are located in intervals of 80 to 200 milliseconds.

Based on the energy, the minimum duration energy limit for each segment (OROSCO et al., 2009) is given by:

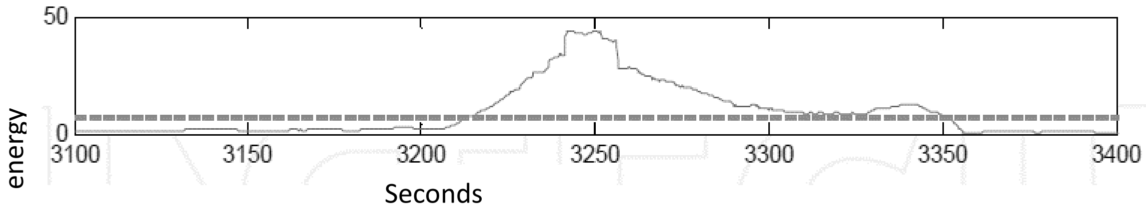
$$Thr = 1{,}0 \times mean(E_{seg}) + 1{,}5 \times standard\ deviation(E_{seg}) \qquad (08)$$

with $mean(E_{seg})$ and $standard\ deviation(E_{seg})$ corresponding to the mean and standard deviation of ith the energy series, of the EEG channel analyzed, while 1 and 1.5 the respective weights.

After the definition of the energy based on the movable overlapping window, an event will be considered epileptic (BAJAJ; PACHORI, 2013), as part of the series of energy that surpasses Thr. The authors sought to determine the events present in the energy of each channel and then identify whether the energy exceeded the limit given in (08).

Also in the preliminary adjustment stage, it was found that when the energy obtained exceeds this limit in at least 8 sub-signals of the first 10 chosen, the analyzed interval presents abnormal EEG patterns. Figure 1 shows when the energy of one of the sub-signals investigated is greater than *Thr* , defined by the dashed line.

Figure 1 – Epileptic event detection through the minimum duration energy limit defined by the dashed line



Next, an interchannel decision is made, i.e., the channels in which the minimum duration energy limit has been exceeded in at least 8 sub-signals are chosen. Based on the methodology applied by Orosco et al. (2009), which seeks to identify the same behavior (energy higher than the minimum duration energy limit) between channels, also in the preliminary adjustment stage of this investigation, it was found that when this behavior occurs in at least 3 channels of the available channels, the interval is considered epileptic.

Contrary to the energy limit being defined by fixed weights for mean and standard deviation, according to (08), the weights for mean and standard deviation were defined for amplitude ranges of the EEG channel analyzed. This is due to the fact that the correct definition of thresholds plays an important role in the performance of the automatic detection of abnormal EEG patterns.

The definition of weights by amplitude ranges, in the training stage, is given by the application of an optimizer with evolutionary mechanism (Solver package in Program R) taking into account a function with the objective of maximizing the number of true-positive (PV), having as decision variables the weights and as a constraint that the sensitivity index (the sensitivity index indicates the ability of the proposed methodology to identify abnormal EEG patterns when they are are present) is greater than 95%, i.e., to identify abnormal EEG patterns when they are present.

From the available database, 50% of the intervals in which the existence of abnormal EEG patterns is known, duly identified and described in the database, was chosen.

After this stage of training with a proposal for improvement, for the test stage the other 50% of the database was used and all events marked as epileptic events made by neurophysiologists and available in the database. The use of this set allows us to verify the generalization of the proposed methodology.

For the purpose of comparison between the performances obtained, fixed weights for the mean and the standard deviation were also used in the calculation of the minimum duration energy, as described in (08).

In the literature, the specificity index indicates the ability to identify normal EEG patterns when present. In this way, the findings of the methodology were compared with the markings made by the neurophysiologists.

RESULTS AND DISCUSSIONS

Table 1 shows the weights obtained in the training phase with a proposal for improvement, responsible for the highest sensitivity and specificity indexes.

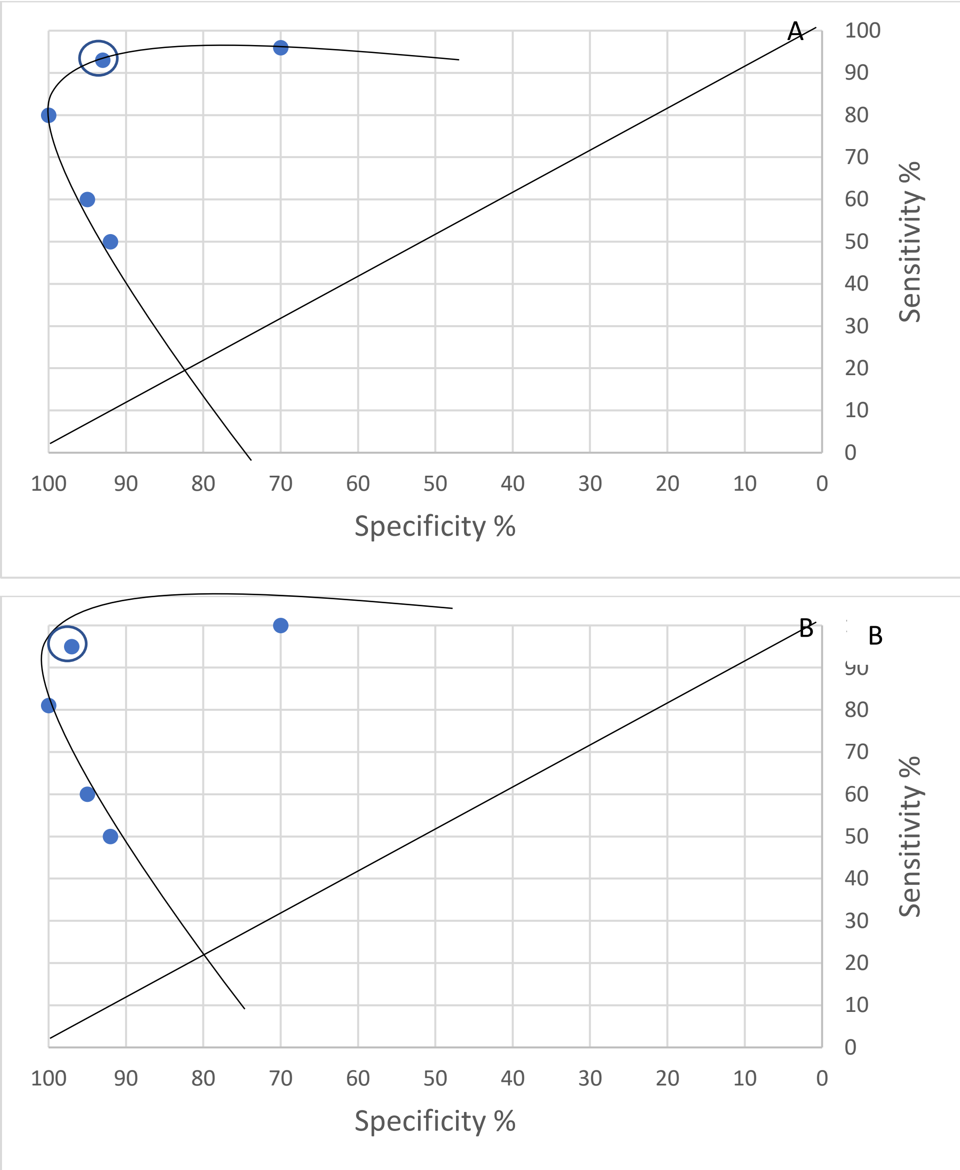
Table 1 – Weights by amplitude range

Range Amplitude in µV	Weight average	Weight Detour Pattern
-20 to 0	6.0	2.6
-40 to -20	5.2	4.0
-60 to -40	7.8	2.9
-80 to -60	8.3	5.4
-100 to -80	1.2	7.7
-120 to-100	2.7	8.9
-140 to -120	6.7	0.8
-160 to -140	6.5	2.0
-180 to -160	1.7	5.9
-200 to -180	8.0	3.1
-220 to -200	5.9	0.0
-240 to -220	0.0	8.0
-260 to -240	5.0	6.6
-280 to -260	4.4	8.0
-300 to 280	3.0	7.4
-320 to -300	4.0	6.3
-340 to -320	1.8	4.5
-360 to -340	4.7	8.6
-380 to 360	3.8	3.8
-400 to -360	7.1	4.0
below -400	9.5	4.3

µV - millionth of a volt

Figure 2 shows the Receiver Operating Characteristic (ROC) curves for the versions with fixed weights (panel A) and weights for different amplitude ranges (panel B). Through the curves it is possible to identify the discriminating power of the proposed diagnostic methodology, whose best value corresponds to 0.96.

Figure 2 – ROC curves with weights by fixed values and weights by amplitude range, respectively from top to bottom, and it is possible to identify in the curves the ordered pairs that describe the behavior of the diagnostic indices, with the optimal combination of sensitivity and specificity located at the top and left of the figures.



In addition to Figure 2, in Table 2, the diagnostic indices help to confirm the best performance for the proposed investigation based on weights by amplitude ranges with 97% sensitivity and 95% specificity when compared with those obtained based on fixed weights. With weights of 1 for mean and 1.5 for standard deviation, in any range of amplitude, the results obtained were 93% sensitivity, 94% specificity, and AUC of 0.94.

Table 2 – Results obtained by the proposed method and in other investigations

Performance indexes	Proposed method weights by amplitude ranges	Proposed method Fixed weights	Orosco et al (2009)	Bajaj E Pachori (2013)	Bergil e Yildiz (2016)
Sensitivity	97%	93%	42%	90%	91%
Specificity	95%	94%	80%	88%	92%
ROC	0,96	0,94	0,55	0,92	0,91

ROC – Receiver Operating Charac

The AESM model and the use of weights for mean and standard deviation in different amplitude ranges to define the energy and the minimum duration energy limit in the detection of abnormal EEG patterns were applied in this investigation. The AESM signal decomposition model, as it is non-parametric and indicated for non-stationary signals, contributes to the resolution of the analysis of non-stationary signals, being able to extract patterns from the signals (SANEI; HASSANI, 2016). By taking into account the existing relationships between the channels, it was also useful for the identification of abnormal EEG patterns in the EEG of epilepsies classified as generalized.

In the proposed methodology, the main argument for the use of weights by amplitude ranges is that the correct definition of thresholds plays an important role in identifying the greatest variability of the signal. This is seen when comparing the results obtained by the investigation when weights were used by amplitude range or when they were fixed according to research already carried out (OROSCO et al., 2009; BAJAJ; PACHORI, 2013; BERGIL; YILDIZ, 2016).

Thus, since abnormal EEG patterns are responsible for high energy, by changing the mean and standard deviation weights to define the minimum duration energy limit, it was possible to obtain the best performance in the automatic detection process.

Although the weights of the mean and standard deviation are fixed, the proposed methodology was able to capture abnormal EEG patterns, showing the potential to assist in automatic detection, in relation to the investigations by Orosco et al. (2009) and Bajaj and Pachori (2013), who also made use of fixed weights to define the minimum duration energy limit and use of the DME model or the investigation that makes use of the entropy and energy characteristics (BERGIL; YILDIZ, 2016) with the application of TDW. Unlike the proposed investigation, all these studies were based on univariate analysis.

Thus, the advantages of the proposed methodology stand out for its multivariate character, when compared to the DME models or TDW application. However, for the investigation, the intervals used are 10 seconds, according to the standard adopted by some neurophysiologists and, thus, making use of a smaller number of samples.

This better performance of the AESM model was possible when verifying other possibilities of fixed weights compared to those obtained by DME and TDW and is also due to the fact that the multivariate analysis is able to identify the harmonics (variability) between a set of signals, ensuring more consistent information about the frequency (SANEI; HASSANI, 2016).

CONCLUSIONS

In view of what has been exposed in the present study, it is evident that the use of EMSA in the proposed methodology proved to be capable of identifying abnormal EEG patterns of epilepsies classified as generalized. The application of different weights for mean and standard deviation of the ith energy series in amplitude ranges improved the detection performance of these abnormal patterns.

In future research, it would be interesting to apply the proposed methodology to EEG signals by applying electrodes placed directly on the exposed surface of the brain during surgery or in a greater number of channels, to promote changes in the extension value in samples of the mobile overlapping window for the calculation of energy in order to verify improvement in the identification of EEG patterns, in addition to reviewing or improving the decisions made in the preliminary adjustments stage.

REFERENCES

1. Alotaiby, T. N., et al. (2014). EEG seizure detection and prediction algorithms: A survey. *EURASIP Journal on Advances in Signal Processing, 2014*(1), 1-22.

2. Bajaj, V., & Pachori, R. B. (2013). Epileptic seizure detection based on the instantaneous area of analytic intrinsic mode functions of EEG signals. *Biomedical Engineering Letters, 3*(1), 17-21

3. Bergil, E., & Yildiz, M. (2016). Comparison of seizure detection performances of features based on wavelet transform and empirical mode decomposition. *Journal of New Results in Science, 16*(6), 288-297.

4. Goldberger, A. L., et al. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation, 101*(23), 215-220.

5. Golyandina, N., & Korobeynikona, A. (2013). Basic singular spectrum analysis and forecasting with R. *Computational Statistics & Data Analysis, 22*, 1-40.

6. Hassani, H., & Mahmoudvand, R. (2013). Multivariate singular spectrum analysis: A general view and new vector forecasting approach. *International Journal of Energy and Statistics, 1*(1), 55-83.

7. Keppenne, C. L., & Ghil, M. (1993). Adaptive filtering and prediction of noisy multivariate signals: An application to subannual variability in atmospheric angular momentum. *International Journal of Bifurcation and Chaos, 3*(3), 625-634.

8. Orosco, L., et al. (2009). An epileptic seizures detection algorithm based on the empirical mode decomposition of EEG. In *Proceedings of the International Conference of the IEEE EMBS*, Minneapolis, Minnesota (pp. 2651-2654). IEEE Publisher.

9. Parreira, F. J. (2006). *Detecção de crises epilépticas a partir de sinais eletroencefalográficos* (Doctoral dissertation, Universidade Federal de Uberlândia). 100f.

10. Patterson, K., Hassani, H., Heravi, S., & Zhigljavsky, A. (2011). Multivariate singular spectrum analysis for forecasting revisions to real-time data. *Journal of Applied Statistics, 38*(10), 2183-2211.

11. Pinheiro, C. A. O., & Senna, V. (2015). Previsão da produção industrial por meio da análise espectral multivariada. *Exacta, 13*(1), 27-43.

12. Plaut, G., & Vautard, R. (1994). Spells of low-frequency oscillations and weather regimes in the Northern Hemisphere. *Journal of the Atmospheric Sciences, 51*(2), 210-236.

13. Runarsson, T. P., & Sigurdsson, S. (2005). On-line detection of patient specific neonatal seizures using support vector machines and half-wave attribute histograms. In *International Conference on Computational Intelligence for Modelling, Control and Automation and International Conference on Intelligent Agents, Web Technologies and Internet Commerce (CIMCA-IAWTIC'06)*, Vienna (pp. 673-677). IEEE Publisher.

14. Sanei, S., & Hassani, H. (2016). *Singular spectrum analysis of biomedical signals*. Boca Raton: Taylor & Francis Group.

15. Scolaro, G. R. (2014). *Sistema computacional automatizado para a identificação e contagem de eventos epileptiformes em sinais de eletroencefalografia de longa duração* (Doctoral dissertation, Universidade Federal de Santa Catarina). 100f.

16. Yoo, J., et al. (2013). An 8-channel scalable EEG acquisition SoC with patient-specific seizure classification and recording processor. *Journal of Solid-State Circuits, 48*(1), 214-228.