Singular Values as a Detector of Epileptic Seizures in EEG Signals

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***Abstract* – This paper introduces a new method based on the Singular Values of EEG signals for the detection of epileptic seizures. Singular Value Decomposition was performed on an EEG signal in epochs of 8 seconds and Singular Values were extracted from each epoch. These singular values were fed into Support Vector Machine (SVM) for a binary classification between epileptic seizure and non- seizure events. Singular Values of EEG signals proved to be a very good feature for the detection of epileptic seizures and gave a classification accuracy of 90%, and an average sensitivity and specificity of 91% and 89%, respectively.**

Index Terms - Electroencephalography (EEG), Epileptic Seizure Detection, Singular Value Decomposition (SVD), Support Vector Machine (SVM).

I. Introduction

Electroencephalography (EEG) is a technique used for the diagnosis of various brain functionalities [1]. The frequency and energy content of an EEG signal carries very important information about the functioning of the brain [2]. Previously, EEG signal analysis was carried out by physicians or neuroscientists by visual inspection of the EEG recordings, but with the recent technological advancements, different computerized algorithms have been developed to analyze EEG signals and prepare automatically a report to help the physicians. This helps the researchers in this area to diagnose the behavior of the signal through different aspects. This advancement in EEG signal analysis has increased the use of EEG by physicians for analyzing the patients having neural disorders. EEG has high temporal resolution (of the order of millisecond) as compared to CT or *f*MRI and that is why it is being used in analysis where high temporal resolution is required [3]. In [4, 5] various non-linear time series methods were applied for the identification of different physiological conditions. In latest trends, EEG is combined with other physiologic signals such as electrocardiogram (ECG) in order to assess the behavior of patient more precisely. In [6] EEG and ECG were combined to find the correlation between the EEG scalp potential and the autonomic nervous system. EEG is in use for the detection and cure of several brain disorders. These disorders include epilepsy, tumors, strokes etc. Among them, Epilepsy is one of the most important and common brain disorder as it affects 1% of the total population in the world [7]. Epilepsy is a chronic disorder of the Central Nervous System. It predisposes a patient to experience recurrent seizures [8]. The use of the EEG signals in the detection of epileptic seizures has a wide scope among researchers in neuroscience field. Many algorithms have been proposed with different degrees of success. In a latest review [1] on seizure detection algorithms a comparison of available algorithms based on EEG and ECG is given. Most of these algorithms use complex features to classify a seizure and a non-seizure activity and thus their computational load is quite high.

Liu *et al.* [9] developed a patient specific algorithm for neonatal epileptic seizure detection. Autocorrelation analysis was used to detect seizures from EEG signals and Scored Autocorrelation Moment (SAM) was used for performance evaluation. The sensitivity and specificity of the system was 84% and 98% respectively.

Gotman *et al.* [10] developed a patient independent algorithm which consists of 3 different methods for feature extraction for rhythmic activity in neonatal EEG. The three methods include calculating the frequency of the dominant peak, multiple spike detection and detection of very slow rhythmic activities. Low pass filtering was also applied as a pre-processing step. The system's average detection rate was 71% with the combination of the three methods with a false detection rate of 1.7 false detection per hour.

Hassanpour *et al.* [11] developed a seizure detection system based on the time-frequency analysis of EEG signals. Left and right singular values were computed from time-frequency distribution of the signals and were squared to be considered as density functions. The dominant features obtained from the histograms were fed to a neural network for classification. The system gave a Good Detection Rate of 92.5 % and False Detection rate of 3.7%.

Wilson *et al.* [12] developed an algorithm for seizure detection called Reveal algorithm. It was based on matching pursuit algorithm and computes matching pursuit decompositions from EEG epochs of two seconds. Each decomposition was represented by its total root mean square amplitude, its maximum amplitude and the summed duration of flat periods corresponding to amplifier saturation. The sensitivity of this system was 76% with 0.11 false detections per hour.

Alkan et al. [13] developed a seizure detection algorithm in which the EEG power spectra was used as an input to the classifier. Different methods were applied for computing the Power Spectral Density of the signals e.g. multiple signal

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classification (MUSIC), autoregressive (AR) and periodogram approaches. Then, different classification methods were applied and compared. 11 patients were used in the study out of which 5 were epileptic. The EEG was recorded using 4 channels namely "F7-C3, F8-C4, T5-O1, and T6-O2". The recordings were annotated by two neurologists to mark the start and end of the seizures. Logistic Regression and Multilayer Perceptron Artificial Neural Networks were used for classification. The results showed that MLP-NN is more robust to noise as compared to LR and gave best results when trained with the Power Spectral Density estimated with the MUSIC method. With this configuration, the classification accuracy was 92%, the sensitivity was 90%, and the specificity was 93.6%.

Greene et al. [14] developed a seizure detection algorithm based on EEG and ECG. The algorithm was evaluated in patient specific as well as patient independent configurations. For the EEG signals, six features were extracted from each EEG channel; "dominant spectral peak, power ratio, bandwidth of dominant spectral peak, nonlinear energy, spectral entropy and line length". For the ECG signals, the R-R interval was calculated first, where; R-R interval is defined as the "time in seconds between two adjacent R-wave maximums". Then the ECG features were extracted, including "mean R-R interval, standard deviation between R-R intervals, mean spectral entropy, mean change in the R-R interval, coefficient of variation and the power spectral density". Both, EEG and ECG features were then fused using early integration and late integration. The results show that in patient specific mode and with early integration fusion the accuracy of proposed method was 86.32%, sensitivity was 76.37%, specificity was 88.77%, GDR was 95.82% and FDR was 11.23%. On the other hand, with late integration fusion the classifier gave an accuracy of 84.66%, sensitivity of 74.08%, specificity of 86.82%, GDR of 97.52% and FDR of 13.18%. In patient independent mode and with early integration fusion the classifier gave an accuracy of 71.51%, sensitivity of 71.73%, specificity of 71.43%, GDR of 81.44% and FDR of 28.57%. With late integration fusion the classifier gev an accuracy of 68.89%, sensitivity of 74.39%, specificity of 66.95%, GDR of 81.27% and FDR of 68.89%.

Aarabi et al. [15] developed a multistage knowledge-based neonatal EEG detection system. The system consisted of multiple stages i.e. band pass filtering and normalizing amplitude of EEG signals, automatic removal of artefacts, segmentation into EEG epochs, feature extraction, feature selection, channel-by-channel classification and integration of the individual channel decisions. Various features were extracted from the EEG segments including time and frequency domains features, autoregressive coefficients, wavelet features and cepstral features. The feature vector was 275 dimensional for each segment and Mutual Information-based Forward Feature Selection (MIFFS) [15] method based on relevance and redundancy was used for feature selection to deduce the feature vector dimensionality. The final feature vector contained "AR coefficients number 3, 6, 12 and 13, the relative spectral power in delta, theta and alpha band, zero crossings of wavelet coefficients, kurtosis of wavelet coefficients, relative energy of wavelet coefficients, mean and coefficient of variation of first derivative of signal, coefficient of variation of amplitudes and curvatures of slow waves, coefficient of variation of durations and curvatures of rapid waves, mean of rise time to fall time of slow and rapid waves, coefficient of variation of durations, slopes and curvatures of spike like waves, mean left side amplitude/mean right side amplitude of slow waves, first and second Hjorth coefficients" [15]. Back Propagation Neural Network with 3 hidden layers was used as a classifier. Overall, training and test performance was measured for classifier giving a sensitivity of 74%, specificity of 70.1% and a false detection rate of 1.55 false detections per hour.

Temko et al. [16] developed a neonatal seizure detection system based on Support Vector Machines. Two post processing steps were proposed for increasing the temporal precision of the system. 55 different features were extracted from frequency domain, time domain and information theory (entropy measures). It was observed during the classification stage that feature selection to reduce the number of features does not significantly reduce the processing time, so all the 55 features were used for classification. At the post-processing stage the output of classifier for input channel was converted to probabilistic values, filtered, and then threshold was applied along with multi-channel decision making to improve the performance of the system. After that, outputs from all channels were combined to make it a multi-channel system. Results showed that the algorithm detected 89% of seizures with 1 false detection per hour, 96% with 2 false detections per hour and 100% with 4 false detections per hour.

In this paper, a novel technique is introduced for early detection of epileptic seizure. The proposed algorithm uses the *r*-singular values of EEG. A sliding window of eight second length with a 50% overlap has been used to indicate seizure related changes in brain behavior. The resulting algorithm is patient-specific and fast enough to be implemented in real-time EEG monitoring.

II. SVD BASED TECHNIQUE FOR SEIZURE DETECTION

The problem considered in this paper is to detect the epileptic seizure for captured EEG signals using m channels. The EEG data record is divided into small windows of n samples each. Consider $\mathbf{A}_{m\times n}$ represents the EEG data matrix of one window. SVD of matrix $\mathbf{A}$ is given according to the following theorem.

For any real $m \times n$ matrix $\mathbf{A}$, there exists a real factorization:

$$\mathbf{A} = \mathbf{U}_{m\times m}.\mathbf{S}_{m\times n}.\mathbf{V}_{n\times n}^{\mathrm{T}} \tag{1}$$

Here matrices $\mathbf{U}$ and $\mathbf{V}$ are real and orthonormal, while matrix $\boldsymbol{S}$ is real pseudo-diagonal with nonnegative diagonal entries.

The diagonal values σ_i of $\mathbf{S}$ are called the Singular Values of matrix $\mathbf{A}$. It is assumed that they are sorted in a decreasing order of magnitude. The columns u_i and v_i of $\mathbf{U}$ and $\mathbf{V}$ are called respectively the left and right singular vectors of matrix $\mathbf{A}$. It is proved with the aid of theorems in [17-19] that some of the first singular values of EEG signals contain the most of the energy of the signals and some of the last singular values contains the lowest energy component of the signals which can be the noise in the signal.

1. $max_{q \in UB} E_q[\mathbf{A}] = E_{u_1}[\mathbf{A}] = \sigma_1^2$

2. $min_{q \in UB} E_q[\mathbf{A}] = E_{u_m}[\mathbf{A}] = \sigma_m^2$

3. $max_{Q^n \subset \mathbf{R}^m} E_{Q^n}[\mathbf{A}] = E_{S_U^n}[\mathbf{A}] = \sum_{i=1}^{n} \sigma_i^2$

4. $max_{Q^n \subset \mathbf{R}^m} E_{Q^n}[\mathbf{A}] = E_{(S_U^{m-n})^\perp}[\mathbf{A}] = \sum_{i=m-n+1}^{m} \sigma_i^2 = 0$

where ‘max’ and ‘min’ denote operators, maximizing or minimizing overall r-dimensional subspaces Q^r of the space $\mathbf{R}^m$. S_U^r is the *r*-dimensional principal subspace of matrix **A** while $(S_U^{m-r})^\perp$ denotes the *r*-dimensional orthogonal complement of S_U^{m-r}.

By establishing this link between the oriented energy and SVD, it is proved that the first *r* left singular vectors senses the maximal energy of matrix **A**, and thus account for most of the variation in the original data. This means that the first *r*-singular values represent the distribution of the energy of matrix into the *m*-Euclidean space. Accordingly, sudden changes in the data will affect the *r*-singular values and redistribute the energy in the *m*-Euclidean space. This characteristic of the singular values will be used to detect sudden changes in EEG signals due to epileptic seizure.

III. METHODOLOGY

The EEG data for 24-peadiatric patients with 198 seizures used in this study was acquired from the PhysioNet Online EEG database [20]. The data was recorded from pediatric patients admitted at the epilepsy monitoring unit of Children’s Hospital Boston. The EEG was captured using 18-channel bipolar montage and sampled at 256 samples/sec.

The EEG data is divided into epochs of eight seconds each. Each matrix contains 18-rows for the 18-channels of EEG and 256×8 columns for 8 seconds of data. The 8 sec window slides forward with a 4 second overlap with the previous window. The SVD is calculated for each matrix and the largest *r*-singular values are obtained. These singular values are then used to train the Support Vector Machine (SVM) for binary classification beteween seizure and non seizure epochs. Polynomial kernel of degree 1 was used with a tolerance parameter of 0.001. Before feeding into classifier, the data was first normalized by dividing each element of the feature vector by the maximum value in that vector. This is done because the singular values are arranged in descending order and there is always a steep decline between the successive singular values. Leave one out cross validation was used with *m*-folds cross validation and *m* being 10. SVM was trained and tested on seizure and non seizure epochs from each patient individually and the results were averaged to get the mean values of the evaluation parameters. This made the system a patient dependent system. To summarize this procedure, the steps of operation are given in Fig 1.

At the classifier output, a confusion matrix is obtained which is used to evaluate the performance of the system. The confusion matrix for an epileptic seizure detection system is shown in Fig 2.

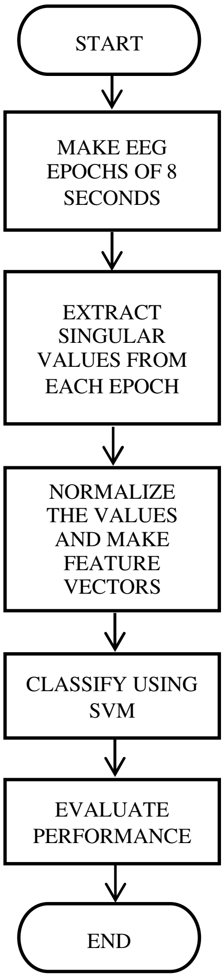

Fig. 1. Methodology Flowchart

		Predicted	
		Epileptic	**Normal**
Actual	**Epileptic**	**TP**	**FP**
	Normal	**FN**	**TN**

Fig 2 Confusion Matrix for Epileptic Seizure Detection

The following parameters were calculated for evaluation:
Accuracy: It is the percentage of the correctly classified instances by the classifier. Mathematically,

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \times 100 \qquad (2)$$

Sensitivity: Sensitivity is the True Positive Rate i.e. the probability of declaration of a seizure event when actually there is a seizure. Mathematically,

$$Sensitivity = \frac{TP}{(TP+FN)} \times 100 \qquad (3)$$

Specificity: Specificity is the True Negative Rate i.e. the probability of declaration of a non-seizure event when actually there is no seizure.

$$Specificity = \frac{TN}{(FP+TN)} \times 100 \qquad (4)$$

IV. RESULTS

The overall classification accuracy was 90.14% which was the average of accuracies obtained for all 24 patients. Similarly, average sensitivity was 91.22% and average specificity was 89.19%. Average false detection rate was 10.81%. Individual results for 24 patients' accuracy, sensitivity and specificity are shown below in figures 3, 4 and 5 respectively.

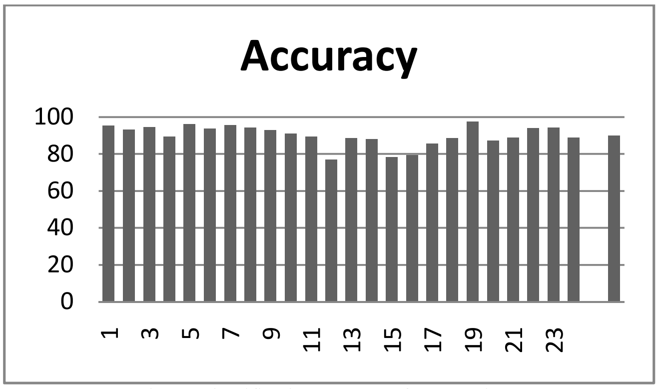

Fig 3. Classification accuracy for 24 patients

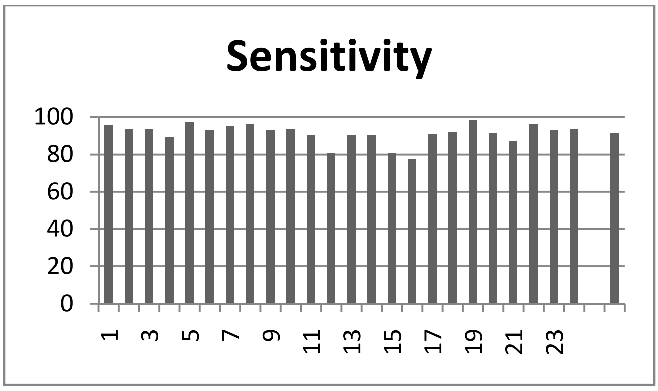

Fig 4. Sensitivity for 24 patients

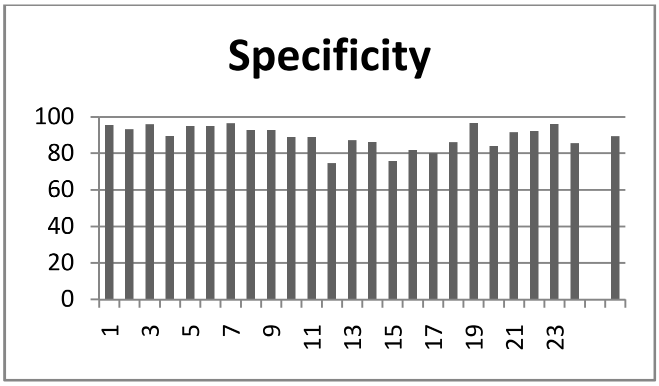

Fig 5. Specificity for 24 patients

Table I Comparison with related studies

Algorithm	Accuracy	Sensitivity	Specificity
Liu *et. al* [9]	n/s	84%	98%
Gotman *et. al* [10]	71%	n/s	n/s
Hassanpour *et. al* [11]	92.5% (GDR)[a]	n/s	n/s
Wilson *et. al* [12]	n/s	76%	n/s
Alkan *et. al* [13]	92%	90%	93.6%
Greene *et. al* [14]	86.32%	76.37%	88.77%
Aarabi *et. al* [15]	n/s	74%	70.1%
Temko *et. al* [16]	89 % (GDR)	n/s	n/s
This work	**90.14%**	**91.22%**	**89.19%**

[a] GDR = Good Detection Rate i.e. percentage of correctly classified seizures
n/s = not specified

Table I shows a comparison of other notable seizure detection algorithms with the Singular Values-based Seizure Detection algorithm presented in this paper. The sensitivity is higher as compared to other algorithms while accuracy and specificity also fairly comparable. This suggests that the proposed technique is able to detect epileptic seizures in EEG recordings and can be modified further to enhance the performance.

V. CONCLUSIONS

Singular Values when used as features to detect epileptic seizures in EEG signals proved to be very good features for classification as they give very good values of sensitivity and specificity. Others available techniques mostly use number of different types of EEG features from time-domain, frequency domain and entropy measures. However this technique only uses a single type of feature i.e. the Singular Values of EEG signals, thus making it a less complex method. This technique can be further optimized to increase the sensitivity and specificity by introducing artifact removal at the pre-processing stage and using Artificial Neural Networks or a combination of different classifiers at the classification stage and thus can be made more efficient for clinical applications.

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REFERENCES

[1] S. Nasehi and H. Pourghassem, "Seizure Detection Algorithms Based on Analysis of EEG and ECG Signals: a Survey," *Neurophysiology,* vol. 44, pp. 174-186, 2012.

[2] A. S. Malik, D. A. Osman, A. A. Pauzi, and R. N. H. R. Khairuddin, "Investigating brain activation with respect to playing video games on large screens," in *Intelligent and Advanced Systems (ICIAS), 2012 4th International Conference on*, 2012, pp. 86-90.

[3] J. W. Phillips, R. M. Leahy, J. C. Mosher, and B. Timsari, "Imaging neural activity using MEG and EEG," *Engineering in Medicine and Biology Magazine, IEEE,* vol. 16, pp. 34-42, 1997.

[4] L. Xia, W. Mumtaz, and A. S. Malik, "Evaluation of EEG features as indicators of physiological conditions," *Australasian Physical & Engineering Sciences in Medicine,* 2012.

[5] W. Mumtaz, L. Xia, A. S. Malik, and M. A. M. Yasin, "Complexity analysis of EEG data during rest state and visual stimulus," in *Neural Information Processing*, 2012, pp. 84-91.

[6] A. R. Subhani, X. Likun, and A. Saeed Malik, "Association of Autonomic Nervous System and EEG Scalp Potential During Playing 2D Grand Turismo 5," in *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, 2012, pp. 3420-3423.

[7] M. Wilde and C. Haslam, "Living with epilepsy: a qualitative study investigating the experiences of young people attending outpatients clinics in Leicester," *Seizure,* vol. 5, pp. 63-72, 1996.

[8] F. Mass, #233, J. Penders, A. Serteyn, M. v. Bussel, and J. Arends, "Miniaturized wireless ECG-monitor for real-time detection of epileptic seizures," presented at the Wireless Health 2010, San Diego, California, 2010.

[9] A. Liu, J. Hahn, G. Heldt, and R. Coen, "Detection of neonatal seizures through computerized EEG analysis," *Electroencephalography and clinical neurophysiology,* vol. 82, pp. 30-37, 1992.

[10] J. Gotman, D. Flanagan, B. Rosenblatt, A. Bye, and E. Mizrahi, "Evaluation of an automatic seizure detection method for the newborn EEG," *Electroencephalography and clinical neurophysiology,* vol. 103, pp. 363-369, 1997.

[11] H. Hassanpour, M. Mesbah, and B. Boashash, "Time-frequency feature extraction of newborn EEG seizure using SVD-based techniques," *EURASIP Journal on Applied Signal Processing,* vol. 2004, pp. 2544-2554, 2004.

[12] S. B. Wilson, M. L. Scheuer, R. G. Emerson, and A. J. Gabor, "Seizure detection: evaluation of the Reveal algorithm," *Clinical Neurophysiology,* vol. 115, pp. 2280-2291, 2004.

[13] A. Alkan, E. Koklukaya, and A. Subasi, "Automatic seizure detection in EEG using logistic regression and artificial neural network," *Journal of Neuroscience Methods,* vol. 148, pp. 167-176, 2005.

[14] B. R. Greene, G. B. Boylan, R. B. Reilly, P. de Chazal, and S. Connolly, "Combination of EEG and ECG for improved automatic neonatal seizure detection," *Clinical neurophysiology,* vol. 118, pp. 1348-1359, 2007.

[15] A. Aarabi, R. Grebe, and F. Wallois, "A multistage knowledge-based system for EEG seizure detection in newborn infants," *Clinical Neurophysiology,* vol. 118, pp. 2781-2797, 2007.

[16] A. Temko, E. Thomas, W. Marnane, G. Lightbody, and G. Boylan, "EEG-based neonatal seizure detection with support vector machines," *Clinical Neurophysiology,* vol. 122, pp. 464-473, 2011.

[17] N. S. Kamel, S. Sayeed, and G. A. Ellis, "Glove-based approach to online signature verification," *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 30, pp. 1109-1113, 2008.

[18] N. Kamel, M. Z. Yusoff, and A. F. M. Hani, "Single-trial subspace-based approach for VEP extraction," *Biomedical Engineering, IEEE Transactions on,* vol. 58, pp. 1383-1393, 2011.

[19] G. H. Golub and C. F. Van Loan, *Matrix computations* vol. 3: JHU Press, 2012.

[20] A. L. Goldberger, L. A. N. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark*, et al.*, "PhysioBank, PhysioToolkit, and PhysioNet: Components of a New Research Resource for Complex Physiologic Signals," *Circulation,* vol. 101, pp. e215-e220, June 13, 2000 2000.