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Epileptic EEG detection using neural networks and post-classification

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ABSTRACT

Electroencephalogram (EEG) has established itself as an important means of identifying and analyzing epileptic seizure activity in humans. In most cases, identification of the epileptic EEG signal is done manually by skilled professionals, who are small in number. In this paper, we try to automate the detection process. We use wavelet transform for feature extraction and obtain statistical parameters from the decomposed wavelet coefficients. A feed-forward backpropagating artificial neural network (ANN) is used for the classification. We use genetic algorithm for choosing the training set and also implement a post-classification stage using harmonic weights to increase the accuracy. Average specificity of 99.19%, sensitivity of 91.29% and selectivity of 91.14% are obtained.

1. Introduction

EEG involves recording and analysis of electrical signals generated by the brain. It is an important clinical tool for diagnosing and monitoring of neurological disorders related to epilepsy. Epilepsy is characterized by sudden recurrent and transient disturbances of mental functions and/or movement of the body that results from excessive discharging of groups of brain cells. Epileptic EEG from the scalp is characterized by high-amplitude and synchronized periodic waveforms [1]. In between seizures, spikes and sharp waves are typically observed. The detection and classification of these activities by visual screening of the recorded EEG is a complex and time-consuming operation and requires highly skilled doctors, who are in great demand. This translates to longer diagnosis time, increase in medical expenditure and consequent delay in necessary treatment. In many cases, epilepsy can be controlled purely by medication. In some other cases, surgical removal of the epileptic part of the brain may be carried out. Newer methods where parts of the brain are electrically stimulated to avoid the onset of seizure are being developed. Automatic detection of seizures forms an integral part of such methods. Therefore there exists a strong need to automate this process.

Most of the work in automatic EEG processing falls into two broad categories—seizure detection and seizure prediction. In 2005, Acir et al. [1] used artificial neural networks for the automatic detection of epileptiform events in EEG signals and compared backpropagation multi-layer perceptron, radial

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basis function network trained by a hybrid method and a support vector method as candidate classifier tools. For training, 7 h 18 min of data from 19 patients were used; while in testing, 3 h 48 min of data from 10 patients were involved. He also correlated the classification outputs from 19 channels. Hostetler et al. [2] compared a commercial spike detecting computer program's performance to six electroencephalographers using six 19-channel EEG recordings of 20 min duration each. One hundred and eighty minutes of 16-channel EEG from 11 patients was used to train an expert system written in a descriptive artificial intelligence language by Dingle et al. [3]. The expert system was tested with the same data used for training. Adjouadi et al. [4] employed Walsh transform to detect epileptic spikes in 21 EEG records of 20–30 min duration. Processing parameters in his algorithm were set using 10 other EEG records. Tzallas et al. [5] used artificial neural networks for detection of epileptic spikes after feature extraction. His data-set comprised of 10–15 min records of 25 patients—half of which were used for training. Breakspear and Williams [6] showed that different techniques of resampling the data in the wavelet domain have great potential for testing non-linear hypothesis in complex non-linear and biophysical systems like isolated spike in background EEG data. A fractal dimension algorithm was used in EEG analysis by Petrosian [7]. An association rule approach has been used for the classification of EEG signals [8], and the auto-SLEX method has been used for preseizure detection of epilepsy in EEG [9]. Iasemidis [10] presented an overview of the application of signal processing methodologies based on the theory of non-linear dynamics and chaos theory to the problem of seizure prediction. Other works of Iasemedis et al. [11–13] provide insight into modern techniques applied to EEG for seizure detection. Kalitzin et al. [14] have used relative phase clustering index (rPCI) to predict epileptic seizure onsets. Litt and co-workers [15] have presented a scheme for quantifying seizure precursors and coupling these measures to brain stimulation for aborting seizures. Sensitivity as high as 90.47% [16] has also been achieved by him in predicting seizures. Reeves and Taylor [17] have used genetic algorithm to choose training sets for neural networks employing radial basis function, to obtain good generalization performance. His networks were trained to solve the XOR problem. We use a similar approach in this paper, but with a backpropagating neural network.

This paper is based on the observation that the EEG spectrum contains some characteristic waveforms that fall primarily within four frequency bands: delta (δ) (< 4 Hz), theta (θ) (4–8 Hz), alpha (α) (8–13 Hz) and beta (β) (13–30 Hz). Many methods such as the Fourier transform (FT) and short-time Fourier transform (STFT) have already been proposed and tested [18,19] for analyzing the signal but they suffer from certain shortcomings.

The FT is incapable of efficiently handling non-stationary signals (EEG in our case). It provides no time resolution [20] and consequently, it is a laborious process to represent transient spikes—which are very common in EEG signals. Furthermore, there is the problem of large noise sensitivity, which demands further computation to resolve.

STFT uses a fixed time–frequency resolution. Increasing the resolution in time decreases the resolution in frequency, and vice versa. That is, once a time window has been fixed, a constant frequency resolution is obtained for the entire time–frequency plane. Since the EEG signal is not deterministic, the problem lies in choosing a computationally efficient time window since the starting and ending time of spectral components are not known beforehand. Testing for a particular window involves translating the window along the whole time scale, which involves a lot of calculation [21]. Consequently we use wavelet transform for feature extraction.

2. Theory of techniques

2.1. *Wavelet transform*

The discrete wavelet transform (DWT) [22] is a versatile signal processing tool that finds many engineering and scientific applications. It has also proven useful in EEG signal analysis [23,24]. DWT is a representation of a signal $x(t)$ using an orthonormal basis consisting of a countably infinite set of wavelets. DWT employs two functions, $\phi(t)$, the scaling function and $\psi(t)$, the wavelet function, which are associated with low- and high-pass filters, respectively. Both of these functions are shifted and scaled as shown below:

$$\forall k, n, k \wedge n \in Z : \phi_{k,n}(t) = 2^{-k/2}\phi(2^{-k}t - n) \tag{1}$$

$$\forall k, n, k \wedge n \in Z : \psi_{k,n}(t) = 2^{-k/2}\psi(2^{-k}t - n) \tag{2}$$

The wavelet representation of a signal $x(t)$ in terms of the scaling and wavelet functions is given by

$$x(t) = \sum_{n=-\infty}^{\infty} c_{k_0,n}\phi_{k_0,n}(t) + \sum_{k=k_0}^{\infty}\left(\sum_{n=-\infty}^{\infty}(d_{k,n}\psi_{k,n}(t))\right) \tag{3}$$

where $c_{k_0,n}$ is called the approximation co-efficient and $d_{k,n}$ is called the detailed co-efficient.The frequency upto which the approximation co-efficients are used for representation of the signal is determined by k_0.

The decomposition of the signal into the different frequency bands as accomplished by the process detailed above, is simply high- and low-pass filtering of the time domain signal yielding detailed and approximation co-efficients respectively. The low pass filter's output is further subjected to the same process of high- and low-pass filtering. This is repeated until the number of levels of decomposition desired is reached. The outputs from both the filters are downsampled at each stage. For this reason, it is to be ensured that the sampling frequency of the signal is at least two times that of the maximum frequency to be analyzed. Selection of suitable wavelet and the number of levels of decomposition is very important in the analysis of signals using DWT. The wavelet can be chosen depending on how smooth the signal is and also on the basis of the amount of computation involved. The number of levels of decomposition is chosen based on the dominant frequency components of the signal. The levels are chosen such that those parts of the signal that correlate well with the frequencies required for classification of the signal are retained in the wavelet co-efficients.

2.2. Artificial neural network (ANN)

The basic units of an ANN are neurons—which are mathematical functions that manipulate input data using weights and biases to produce an output. These neurons can be organized in groups which may then be cascaded, thus forming multi-layered networks. A feed-forward backpropagating neural network involves supervised learning, in which the computed outputs from each neuron move forward to other layers until finally an output is formed. The backpropagation technique then adjusts the weights and biases repeatedly so that the computed output is close to the expected output—as determined by the mean-squared error (MSE) value. The manner in which the randomly initialized weights and biases change is determined by training algorithms, such as the Levenberg–Marquardt (LM), resilient backpropagation (RP) and the quasi-Newton algorithms. These algorithms vary in their convergence speed, memory requirement and total time to train. Although the Levenberg–Marquardt algorithm converges fast [25], it is memory-intensive, and hence we choose the resilient backpropagation algorithm for training. The training process stops when either the performance goal is met or the maximum number of epochs is reached.

2.3. Genetic algorithm

The genetic algorithm [26] is a search technique used in computing to find exact or approximate solutions to optimization and search problems. They are a particular class of evolutionary algorithms that use techniques inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. These are commonly implemented as computer simulations where a population of abstract representations (called chromosomes) of candidate solutions to an optimization problem, evolve towards better solutions. Traditionally, solutions are represented in binary as strings of 0 s and 1 s, but other encodings are also possible. The evolution usually starts from a population of randomly generated individuals and gives rise to new generations. In each generation, the fitness of every individual in the population is evaluated based on the solution provided by it. Subsequently, multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. The algorithm terminates when either a maximum number of generations has been produced, a satisfactory fitness level has been reached for the population or when no improvement is seen in the solution to the problem after a certain number of generations. We use a binary representation of the chromosome to indicate whether or not a particular EEG recording is used in the training set. The fitness of the chromosome is then updated based on the value of the seizure detection sensitivity. The algorithm terminates if there is no improvement in the sensitivity value after 200 successive generations.

3. Design considerations

Any attempt at automating epileptic EEG detection should in general satisfy the following requirements:

- The system should be able to train/learn from the small amount of epileptic data that is usually available. Clinical EEG recordings usually have long hours of non-epileptic data with relatively short durations of epileptic activity.
- While the time taken to train the system is not of much concern, it must be made as short as possible. This is because the system would have to be trained only once.
- If used for real-time detection, the time taken by the system to process EEG data and produce an output should be small.
- The system should have good accuracy. This can be in the form of specificity, sensitivity, selectivity or other performance ratios.
- It is an added advantage if the same system is capable of detecting different types of epilepsies in multiple patients.
- Finally, the whole system should be low on resource demand and simple enough for easy and large-scale implementation.

4. System description

4.1. Data set

Our EEG database has been obtained from the website of the Albert-Ludwigs-Universtãt, Freiburg, Germany [27] and contains invasive EEG recordings of 21 patients suffering from medically intractable focal epilepsy. The data was recorded during an invasive pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg, Germany. In 11 patients, the epileptic focus was located in neocortical brain structures, in eight patients in the hippocampus, and in two patients in both. In order to obtain a high signal-to-noise ratio, data with artifacts were removed. To record directly from focal areas, intracranial grid, strip, and depth electrodes were utilized. The EEG data was acquired using a Neurofile NT digital video EEG system with 128 channels, 256 Hz sampling rate, and a 16 bit analogue-to-digital converter. For each of the patients, we use an “ictal” dataset containing recordings with epileptic seizures, atleast 50 min of recording before seizure onset and atleast 50 min of recording after the seizure stops. These recordings made before and after the seizure are termed pre-ictal data. An average of 7.73 min of epileptic data is available per patient—with a single seizure duration varying from 4 s to 28 min. Figs. 1 and 2 show the ictal and pre-ictal recordings from a patient. The “interictal”

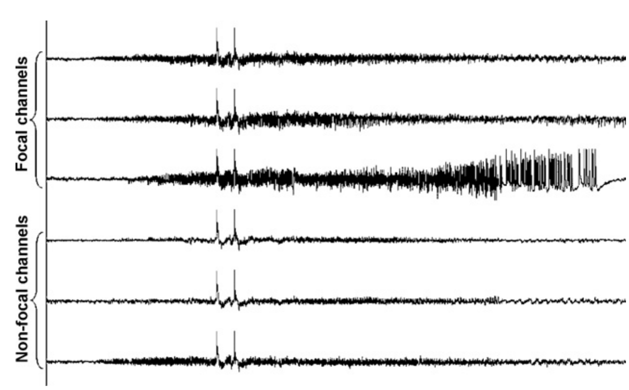

Fig. 1 – Ictal EEG: 147 s of ictal EEG from six channels.

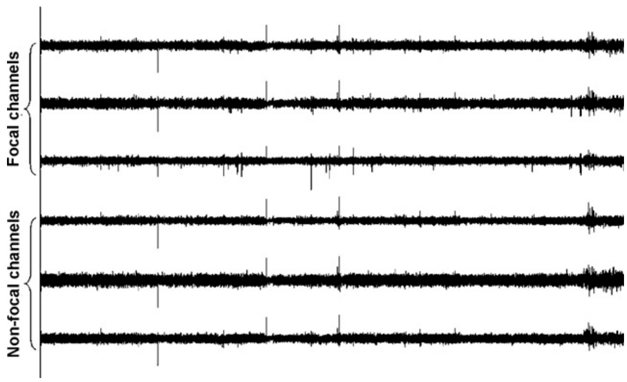

Fig. 2 – Pre-ictal EEG: 57.54 min of pre-ictal EEG from six channels.

dataset (Fig. 3) contains approximately 24 h of EEG recordings without seizure activity. At least 24 h of continuous interictal recordings were available for 13 patients. For the remaining patients, interictal invasive EEG data consisting of less than 24 h were joined together, to end up with at least 24 h per patient. Thus, one recording corresponds to 1 h of data from one channel. The six contacts of all implanted grid, strip and depth electrodes were selected by visual inspection of the raw data by a certified epileptologist. Three contacts were chosen from the seizure onset zone, i.e. from areas involved early in ictal activity. The remaining three-electrode contacts were selected such that they were not involved or involved last during the seizure spread. The seizure periods were determined based on identification of typical seizure patterns preceding clinically manifest seizures in intracranial recordings by visual inspection of experienced epileptologists.

4.2. *Processing*

4.2.1. *Filtering*

In order to restrict the EEG signal within the desired frequency band (encompassing the δ, θ, α and β waves), to remove line noise due to electric supply, and to remove stray spikes due to noise, we undertake filtering of the signal. We use a fourth order butterworth bandpass filter with lower and upper cut-off frequencies of 0.35 and 30.5 Hz, respectively. After filtering once, the signal is reversed and filtered again to nullify phase shifts.

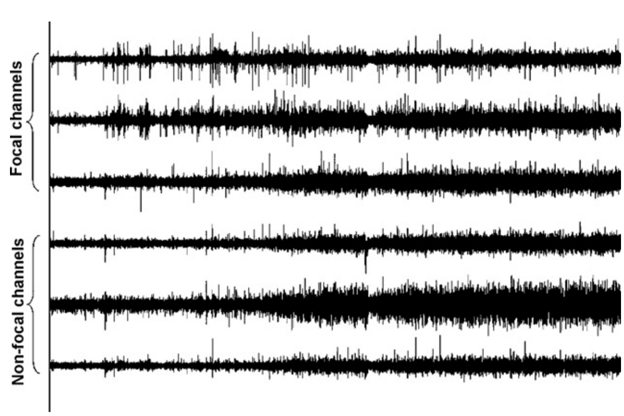

Fig. 3 – Interictal EEG: 1 h of interictal EEG from six channels.

Table 1 – Decomposed wavelet co-efficients and corresponding frequency bands

Decomposed signal	Frequency range (Hz)
D1	64–128
D2	32–64
D3	16–32
D4	8–16
D5	4–8
A5	0–4

4.2.2. *Normalization*

We first partially normalize the EEG signal x by using a scaling factor s defined by

$$s = (|\bar{x}| + \sigma_x) \tag{4}$$

where σ_x is the standard deviation of the EEG signal and $|\bar{x}|$ is the mean of the absolute value. Assuming that the EEG signal amplitude has a normal distribution [28], the scaling process results in a partial normalization. Statistically, $(\sigma_x + \bar{x})$ is greater than 68% of the signal. But since we use $(\sigma_x + |\bar{x}|)$, the percentage of signal lying in $[-1, +1]$ would be considerably higher. To make the normalization more robust, we use a non-linear hyperbolic tangent sigmoidal function defined as

$$g(x) = \frac{2}{1 + e^{-2x}} - 1 \tag{5}$$

The advantage of this two-step process is that the first step ensures that the algorithm works across different data sets where amplitudes may be scaled by different values. Consequently, our statistical parameters are not adversely affected. The second step completely fits the signal into $[-1, +1]$ with the added advantage that it enhances the amplitudes of those parts of the signal which may have been drastically reduced because of sharp spikes – normal or abnormal – in the EEG. Although the hyperbolic tangent sigmoidal function is essentially non-linear, we observed an average increase of around 20% in specificty, sensitivity and selectivity after adding this to our processing algorithm.

4.2.3. *Windowing and wavelet decomposition*

Each EEG signal is divided into a 4 s window with a 3 s overlap between consecutive windows. This means that for processing 1 s of EEG data, we also use the previous 3 s as part of the window. These durations were arrived at after extensive testing with various window and overlap lengths.

As mentioned before, EEG signals show characteristic waveforms in δ, θ, α and β ranges. Since our data is sampled at 256 Hz, we choose a level 5 wavelet decomposition so that each frequency range is almost completely represented by an individual co-efficient. Table 1 shows the frequency bands that the detailed (D1–D5) and approximation (A5) co-efficients represent.

From Table 1 it can be seen that A5 corresponds to the δ range, D5 to the θ range and so on. The co-efficients represent the amplitude of the combined signals in their frequency

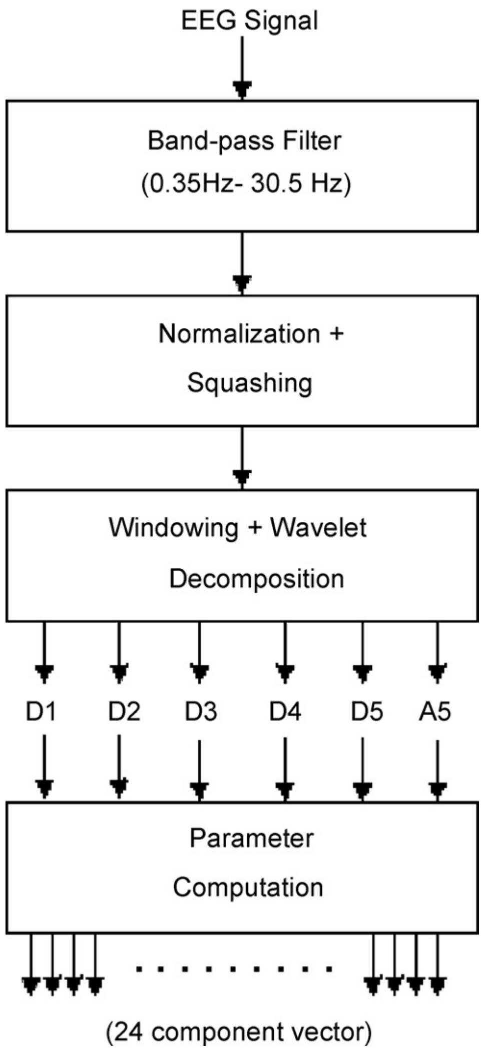

Fig. 4 – Pre-processing stages and feature extraction.

bands. Once the wavelet decomposition is done, we compute the following simple statistical parameters for each time window in all the decomposed co-efficients:

(1) mean: corresponds to the constant or DC signals at various frequency ranges;
(2) absolute mean: for tracking both DC signals and alternating or ac signals;
(3) root mean squared (RMS) value: to measure power of the signal in the window;
(4) standard deviation: to represent the level of fluctuation of the signal.

Since we have six decomposed co-efficients and four parameters, each time window is represented by a vector with 24 elements. Fig. 4 gives a brief overview of the above steps.

4.3. *Neural network training*

Normally, EEG data are classified as ‘epileptic’ or ‘normal’. In our case, as mentioned in Section 4.1, epileptologists have classified the data into *three* categories—ictal, pre-ictal and interictal. We exploit this grouping to achieve our primary objective of detecting purely epileptic signals. Thus, our ANN classifies EEG data into three classes. Consequently our training set consists of three categories. Since our processing scheme uses a 4 s window, we include 3 s of EEG data before and 1 s after epileptic seizures and use this resulting signal as training set for the ictal class. We train and test the ANN classifier for each patient individually, i.e. a network trained using data from one patient is not used for testing data from another patient.

The choice of the data used for training is a very important one. Sensitivity as low as 3% was observed with an inappropriate training set. Although we do not define what constitutes an appropriate training set, we experimentally resolve this issue using a genetic algorithm. We restrict the number of training signals to six each for interictal, pre-ictal and ictal activities. This translates to 6 h of normal data, a few minutes of ictal data (depending on the duration of the signals chosen) and roughly 6 h of pre-ictal data. Six signals were chosen in each case to reduce the training time taken by the neural network and to allow the possible inclusion of all the six channels of data from a particular hour of recording. The neural network training set is chosen by the genetic algorithm, which tries to maximize the sensitivity. For every iteration of the genetic algorithm, it is allowed to choose six signals per category from a set containing 80% of the available data per patient. The remaining 20% is ‘hidden’ from the genetic algorithm and from the neural network. During the execution of the genetic algorithm, neural network testing uses data from the reserved set alone, i.e. the 20% ‘hidden’ data is not tested. This is done so that the sensitivity can be maximized by the genetic algorithm within a limited set of possible training vectors. This also prevents over-fitting of the neural network. Thus, upon termination of the genetic algorithm, the neural network training set has six signals per category which are optimal for the set containing 80% of the available data. It may be noted at this stage that although an optimal training set has been found, this does not necessarily imply numerically high values of sensitivity. The genetic algorithm only maximizes the sensitivity while the exact numerical values are due to the efficiency of our main processing algorithm (including post-classification). The above steps are depicted in Fig. 5.

The ANN used is a two-layered feed-forward backpropagating network with 10 neurons in level 1 and 3 neurons in level 2 (Fig. 6). Both levels use a hyperbolic tangent sigmoidal squashing function. Resilient backpropagation algorithm is used for training. We set the maximum number of epochs as 1000 and the performance goal (MSE) as 10^{-5}. Initial tests with the above architecture and parameters were both faster and more accurate when compared to other architectures having lower MSE values and using different number of neurons in level 1. Three neurons are used in level 2 following our requirement of having three categories for classification. Each neuron fires when it encounters signals corresponding to one of the three categories.

4.4. *Neural network testing*

Testing is carried out on the optimally trained neural network using all the data available per patient. By testing with

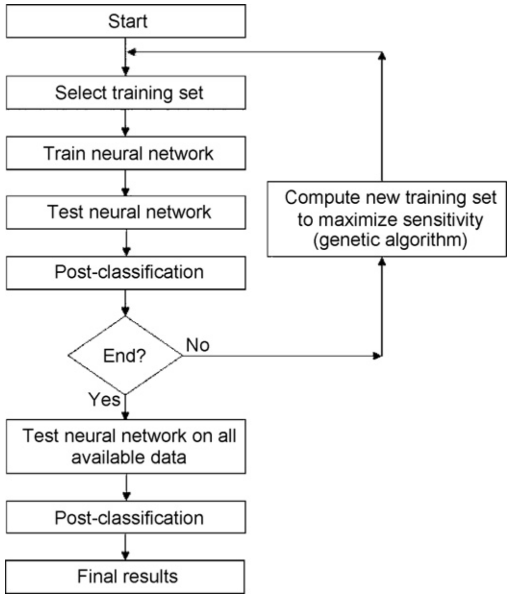

Fig. 5 – Brief flowchart of the overall algorithm.

the 'hidden' data, an estimate of our algorithm's performance is obtained when it is presented with totally new data. At the same time, testing with the 80% of data reserved for the genetic algorithm is meaningful because in effect, the training set for the neural network comprises of only the six optimal vectors from each category. Hence testing the algorithm over all the data available does not present an inaccurate account of the algorithm's performance. Each channel from a subject is individually fed to the classifier after processing and the results obtained are fed to the post-classification stage for integration of outputs from multiple channels. The outputs from the classifier are numerical values p_1, p_2 and p_3 corresponding to the three categories of the signal - interictal, pre-ictal and ictal, respectively. We choose $p_1 = +1$, $p_2 = -1$ and $p_3 = -5$. These are chosen based on the post-classifier algorithm which needs p_1 and p_2 to be of opposite signs, preferably with the same magnitude, and p_3 to be of the same sign as p_2 but with higher magnitude.

4.5. *Post-classification*

For 1 h of EEG recording, the classifier uses six channels of data and outputs six classification result vectors. We present below the framework of our algorithm to correlate the six output

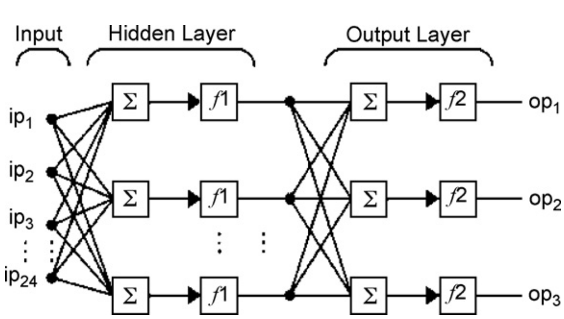

Fig. 6 – Basic structure of neural network used.

vectors. Specific numerical values used by us are indicated, but these may be varied.

(1) Define weight-vector-alpha = $(\alpha_1, \alpha_2, \ldots, \alpha_n)$ where the constant n is the desired number of previous outputs that are used for processing a particular output at position $(n+1)$ (we call this current-output). α_i s form an increasing harmonic series starting at a convenient value, which depends on the number of mis-classified signals from the ANN classifier that the post-classifier algorithm is allowed to correct before accepting the ANN classifier's output as the true classification result. We set $n = 10$, $\alpha_1 = 1/20, \alpha_2 = 1/19, \ldots, \alpha_{10} = 1/11$.

(2) Define weight-vector-beta = $(\beta_1, \beta_2, \ldots, \beta_n, \beta_{n+1})$ where β_i are weights following a similar pattern as α_i, but with lesser magnitude. Note that β_{n+1} corresponding to current-output is also included in the weight vector. We set $\beta_i = \alpha_i^2$. Thus, $\beta_1 = 1/400, \beta_2 = 361, \ldots, \beta_{11} = 1/100$.

(3) Find the sum of the ANN classifier output for each channel and call this net-output. A lower weight $\lambda = 0.5$ is used for the output from channels that are not involved or involved last in seizure activity. Thus outputs from three channels in our case are weighted using λ. The other three channels are directly added.

(4) Using net-output, extract the array $(v_1, v_2, \ldots, v_n, v_{n+1})$ where current-output is v_{n+1}, and find its weighted sum. Use the corresponding weight from the associated weight-vector for each v_i. If a weight-vector is not yet associated with a particular v_i, use weight-vector-alpha and the corresponding α_i as weight. Always use β_{n+1} as the weight for v_{n+1}.

(5) Multiply the weighted sum from the above step with v_{n+1}.

(6a) If the sign of the result is positive, apply thresholds to current-output to obtain the final classification. Using our values of p_1, p_2 and p_3, a value of current-output greater than zero is labeled *interictal* and more than kp_3 but less than zero is labeled *pre-ictal*. We use $k = 2 + \lambda$, thereby requiring atleast two focal electrode channels and one other channel to have detected epileptic activity. Values of current-output lower than kp_3 represent epileptic activity and are labeled *ictal*. Finally, we associate weight-vector-alpha with current-output.

(6b) A negative sign to the result indicates that current-output is a misclassification by the ANN. If current-output is greater than zero, it is labeled *pre-ictal*, otherwise it is labeled *interictal*. Also, weight-vector-beta is associated with current-output. Thus, although a particular ANN classifier output may be wrong, we still consider it for post-classification processing, but with a lower weight.

(7) Advance the position of current-output to the next element in net-output. While this retains the associated weight vector for each element of net-output, the corresponding weight for that element will be determined by the element's position in the array $(v_1, v_2, \ldots, v_n, v_{n+1})$ which would be extracted in the next iteration. This process is continued until the end of net-output is encountered in the extracted array $(v_1, v_2, \ldots, v_{n+1})$, indicating that all outputs corresponding to 1 h of six channel EEG recordings have been processed.

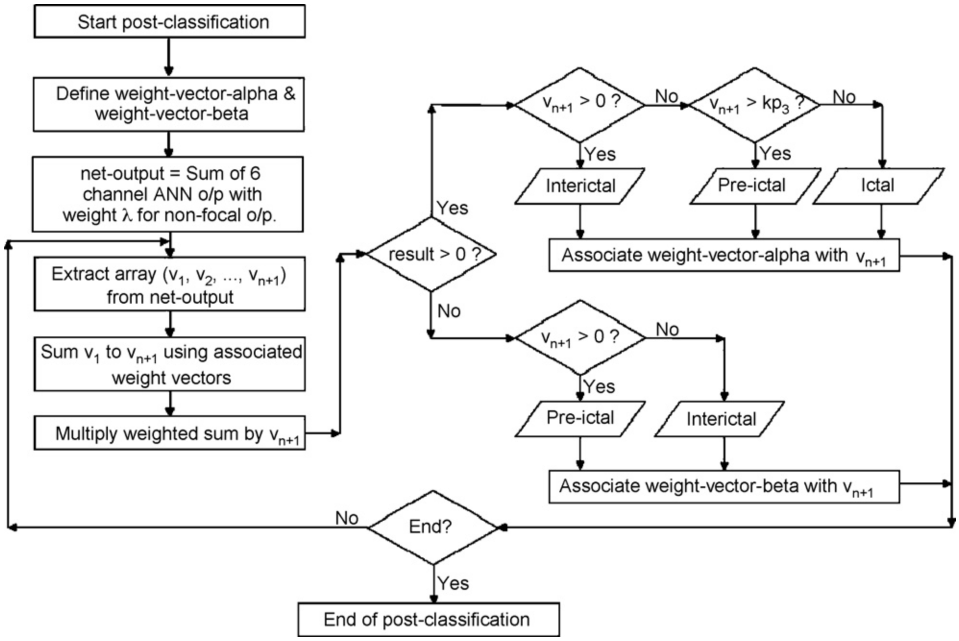

Fig. 7 – Flowchart of post-classification stage.

Fig. 7 depicts the post-classification algorithm detailed above. This algorithm uses current-output and n outputs before this, to decide if current-output is a mis-classification by the ANN classifier. A harmonic series is used for the weights α_i so that the n previous outputs are weighted in such a way that older outputs are given lesser priority; but at the same time, small groups of newer outputs that are possibly wrong do not adversely affect the post-classifier's output. It may be noted that weights which are part of a geometric series do not have the second property mentioned.

4.5.1. *Further increasing sensitivity*

The above algorithm uses a simple threshold kp_3 to distinguish between ictal and pre-ictal signals in step 6(a). Due to this, in some cases, parts of an epileptic EEG signal may be wrongly labeled as pre-ictal. To overcome this, we modify our post-classification algorithm using the following:

- Define future-weight=$(\alpha_n, \alpha_{n-1}, \ldots, \alpha_{n-m+1})$, where $m(\leq n)$ is the number of classifier outputs occurring after current-output in the net-output vector, that are used for processing. α_i are as defined in weight-vector-alpha. We use $m = 10(= n)$.

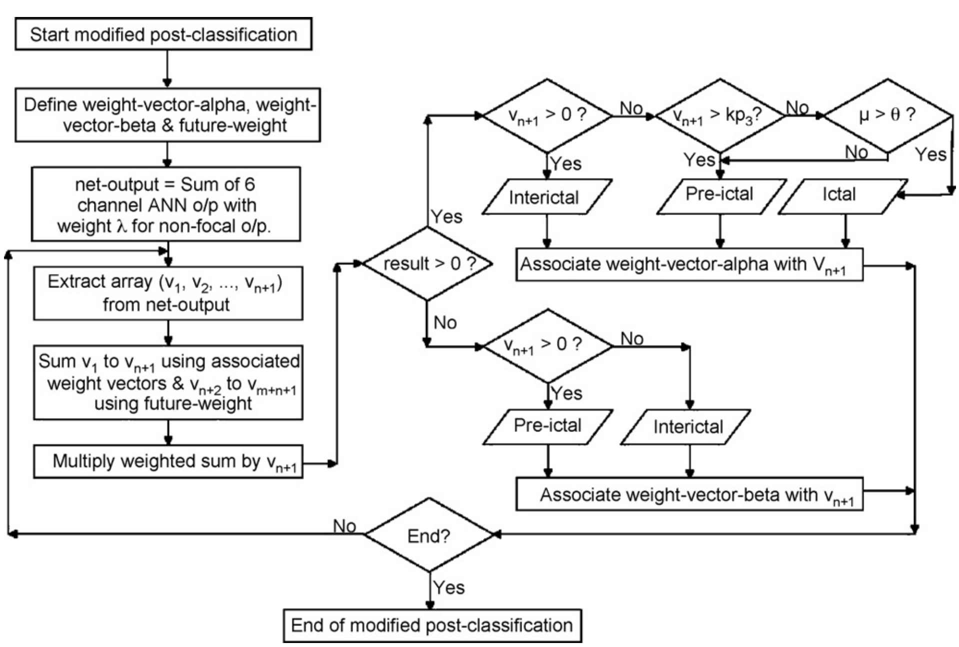

Fig. 8 – Flowchart of modified post-classification stage.

- Compute μ, the weighted sum of m outputs ($v_{n+2}, v_{n+3}, \ldots, v_{m+n+1}$) using the corresponding weights from future-weight vector (i.e. compute $v_{n+2}\alpha_n + v_{n+3}\alpha_{n-1} + \cdots + v_{m+n+1}\alpha_{n-m+1}$). Along with the kp_3 threshold of step 6(a), μ is compared to a threshold θ ($p_3\{1/11 + 1/12 + \cdots + 1/15\}$ in our case) and only if it is found to be higher, the output is labeled as *ictal*. Failing this, even if current-output is greater than kp_3, it is labeled *pre-ictal*. The value of θ needs to be set considering the minimum duration of epileptic seizures, which is 6 s in our case.

Fig. 8 depicts the final post-classification algorithm after modifications. The post-classification algorithm without the above modification increased the sensitivity of detection by 6% while retaining the algorithm's capability of processing real-time signals. The above modification is seen to increase the sensitivity by a further 2%. It is to be noted though, that the modification renders the algorithm incapable of processing real-time signals. Thus, the algorithm, would then be restricted to detecting epileptic activity in pre-recorded EEG data.

We use the algorithm detailed above along with the modification in the post-classification algorithm to train and test our system. Since our main objective is to detect epileptic seizures, we do not distinguish between interictal and pre-ictal labels for performance measurement, i.e. we group both these classes into a 'non-epileptic' category. Nonetheless, classification into three categories greatly helps our post-classification algorithm, and is seen to give a better overall performance.

4.6. *Implementation of algorithms*

The algorithm was run on a desktop computer with 3.0 Ghz Intel micro-processor, 1 GB of 533 Mhz DDR2 memory and 80 GB SATA Hard Disk. This computer was used for the neural network training. In all, we use roughly 24 h of EEG data per channel per patient for testing. Processing these signals to generate the 24-element representative vector from the windowed wavelet co-efficients involves a lot of computation owing mainly to the long duration of recordings. But since the computation can be carried out in parallel upon multiple signals, we use a high-performance computational cluster consisting of 15 nodes, all with the same specifications as the desktop computer, which we use as the master for controlling the cluster nodes. The master and nodes are connected by gigabit ethernet Network Interface Cards. The master and all the nodes run on RedHat Enterprise Linux v4. Software implementations are carried out in MATLAB R2007a, installed on all systems. Wavelet decomposition and the neural network classifier were both implemented using the in-built toolboxes.

5. Results

Average time to process one EEG signal of 1 h duration was 16.92 s; 4.7 ms to process 1 s of EEG signal. It may be noted that the algorithm produces an output for every second of input EEG data.

Table 2 – Results of testing the algorithm using data from 21 patients

Patient no.	Specificity (%)	Sensitivity (%)	Selectivity (%)
1	98.91	89.67	90.12
2	99.67	91.65	93.10
3	99.46	92.34	93.86
4	98.97	92.31	91.54
5	99.12	93.16	91.84
6	98.52	89.68	90.33
7	99.06	91.28	89.56
8	99.18	93.80	88.67
9	98.87	88.38	91.17
10	99.82	90.91	92.95
11	98.61	91.60	93.12
12	99.13	90.74	91.38
13	99.63	92.82	90.70
14	99.45	87.73	89.63
15	99.28	93.21	87.58
16	99.56	92.14	90.27
17	99.79	90.88	92.34
18	98.56	89.34	91.61
19	99.63	91.72	89.81
20	99.47	91.49	90.65
21	98.32	92.18	93.70
Average	**99.19**	**91.29**	**91.14**

We present our results in terms of the following accuracy measuring ratios : sensitivity, specificity and selectivity. Mathematically,

$$\text{specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100\% \tag{6}$$

$$\text{sensitivity} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100\% \tag{7}$$

$$\text{selectivity} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100\% \tag{8}$$

where TP-true positive, FN-false negative, TN-true negative and FP-false positive.

TP is the number of epileptic signals detected correctly by the algorithm, i.e. same result as obtained by a trained doctor in detecting seizure. TN is the number of normal signals detected correctly. FP is the number of normal signals labeled epileptic by the algorithm and FN is the number of epileptic signals labeled normal by the algorithm.

As we train and test our algorithm for each patient individually, we present the classification results of all the 21 patients whose EEG data were analysed in Table 2. We also indicate the average specificity, sensitivity and selectivity obtained.

Table 3 presents an overall comparison of our method with a few other detection methods. The results are presented in terms of specificity, selectivity and sensitivity, wherever available. It can be seen that our algorithm performs better than previous attempts at automation.

6. Strengths and weaknesses of the proposed algorithm

The major strengths of our algorithm are

Table 3 – Comparison with other automatic seizure detection attempts

Author	Sensitivity	Selectivity	Specificity
Acir et al. [1]	89	86	–
Hostetler et al. [2]	59	89	–
Dingle et al. [3]	53	100	–
Adjouadi et al. [4]	82	92	–
Tzallas et al. [5]	80–85	77–90	90–97
Exarchos et al. [8]	84	82	91
Our method	**91.29**	**91.14**	**99.19**

- Having used wavelets for feature extraction, we compute simple statistical parameters from the wavelet co-efficients and use these parameters to represent the EEG signals. This is not computationally intensive, even for real-time signals.
- A genetic algorithm has been used for choosing the training set, as opposed to the common method of randomly selecting data for training. We observe a consequent increase in our accuracy ratios due to this.
- The post-classification algorithm correlates the ANN classifier output over multiple channels (six in our case) and yields a single classification label. It is seen to have the following advantages:
  - It provides a simple yet efficient means of relating multiple outputs for the same duration of the EEG signal. Data from electrodes placed outside the epileptic focus usually show low epileptic activity after ANN classification. This has been taken into consideration by assigning an appropriate weight.
  - It eliminates improper classification outputs over short periods which may occur due to low-power noisy disturbances. Thus it avoids short durations of pre-ictal activity being detected in interictal regions of the signal and vice versa.
  - In many cases, epileptic activity lasts only for a short time. To be able to detect this, while still retaining the previously mentioned advantage, we use a high magnitude for p_3. At the same time, the value of p_3 is low enough for the algorithm to not allow labeling of signals as *ictal* unless some duration of *pre-ictal* signal has already been encountered.
  - In other techniques such as moving average filter or simple low pass filter, the resulting values need to be further quantized which demands additional thresholding rules. Also, short durations of mis-classified outputs may adversely affect the neighboring classification results depending on the filter order and the output value of the algorithm for each class. These problems have been eliminated to a certain extent in our algorithm.
- The reasonably high specificity, sensitivity and selectivity values obtained show that our processing algorithm for feature extraction and our post-classification stage both perform well.

There are also certain weaknesses in our algorithm which need to be overcome.

- Although a definite increase in the accuracy ratios is observed, the genetic algorithm used for choosing the training set takes a long time to terminate. This increases the time for optimally training the system by many hours. Note that we have not made any attempts to optimize the genetic algorithm. More work in this direction may reduce the training time.
- Currently, after our system has been trained using data from one patient, an average decrease of around 10% in specificity and 18% in sensitivity is observed when tests are carried out using data from other patients, having different epileptic foci. This indicates that upto a certain level, all types of epileptic seizures show up similarly in the EEG recordings. This possibility needs to be further explored.
- A further increase in sensitivity and selectivity is a must for clinical deployment of such a system.

7. Conclusions and discussion

Detection of epileptic activity in EEG recordings is mostly done by a small number of skilled professionals today. Automating this process presents many advantages and among them are faster diagnosis, non-stop monitoring, and reduction in overall cost of medical treatment. Automatic intervention of systems by electrical stimulation of the brain to prevent onset of seizures would also benefit from such work. We propose a wavelet-based feature extraction technique which consequently uses simple statistical parameters to detect epileptic EEG signals using a backpropagating artificial neural network classifier. We also employ a post-classification stage to correlate the outputs from different channels and also to increase the overall accuracy (specificity, sensitivity and selectivity). Average detection sensitivity of 91.29%, specificity of 99.19%, and selectivity of 91.14% are obtained. Considering the speed of our algorithm (4.7 ms for wavelet decomposition and statistical computation and a classification time of 0.012 ms with ANN for one 4 s window with 3 s overlap), implementing this for real-time epileptic EEG detection also seems feasible, provided the modification in the post-classification algorithm is not included. As mentioned before, the post-classification algorithm's modification uses outputs occurring in the future to increase sensitivity.

8. Future work

Automation of epileptic EEG signal detection is a daunting task and although much work has been done in this field, the search for an algorithm that performs well across multiple patients with different types of epileptic seizures is still on. Although we have used only a few basic techniques in this paper, our accuracy seems higher than those of other similar attempts. Apart from addressing the weaknesses that we have mentioned, our algorithm's performance can probably be improved by using better techniques of choosing training sets for the neural network, using more statistical parameters for each time window, employing a different type of neural network (supervised or unsupervised), and by varying the parameters used in the post-classification stage.

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