A neural-network-based detection of epilepsy

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Diagnosis of epilepsy is primarily based on scalp-recorded electroencephalograms (EEG). Unfortunately, the long-term recordings obtained from ambulatory recording systems contain EEG data of up to one week duration, which has introduced new problems for clinical analysis. Traditional methods, where the entire EEG is reviewed by a trained professional, are very time-consuming when applied to recordings of this length. Therefore, several automated diagnostic aid approaches were proposed in recent years, in order to reduce expert effort in analyzing lengthy recordings. The most promising approaches to automated diagnosis are based on neural networks. This paper describes a method for automated detection of epileptic seizures from EEG signals using a multistage nonlinear pre-processing filter in combination with a diagnostic (LAMSTAR) Artificial Neural Network (ANN). Pre-processing via multistage nonlinear filtering, LAMSTAR input preparation, ANN training and system performance (1.6% miss rate, 99.4% overall accuracy when considering both false alarms and 'misses') are discussed and are shown to be favorably with earlier approaches presented in recent literature. [Neural Res 2004, 26, 55-60]

Keywords: Epilepsy; medical diagnosis, automated diagnosis, neural networks (NN); LAMSTAR NN; pre-filtering; nonlinear filtering

INTRODUCTION

Epilepsy is the most common serious neurological disorder with 3% - 5% of the population suffering at some time of their life and approximately 1% having established epilepsy. A person is diagnosed as epileptic if he suffers from a recurrent tendency to have seizures (a single seizure is not epilepsy). Epilepsy leaves its signature in the electroencephalogram (EEG). Detection and prediction of epilepsy is based on long term monitoring and analysis of the EEG, but since onset of seizures cannot be predicted in the majority of cases, continuous recording of EEG is quite common. A common form of recording is ambulatory recording. However, analysis of long recordings of EEG is time consuming (1). Hence a need for automated detection of epilepsy has been sought by many researchers for a long time.

Since EEG recordings are now recorded digitally for viewing on a computer display unit they also lend themselves to automatic analysis. The benefits of permitting a first pass on the data with an automatic seizure detector are clear - if the amount of data presented to the technician can be reduced then more patients can be treated. Even within the inpatient recording environment an automatic detection system can prove advantageous. Salinsky reported, in a study of 83 patients admitted for in-patient monitoring, that 22% of the seizures recorded were captured only by the computer detection system, resulting in an estimated saving of 1.3 hospital days per admission (2). In a case of epilepsy, two categories of abnormal activity are observed in the EEG: ictal (during an epileptic seizure) and inter-ictal (between seizures). The most common form of inter-ictal abnormality is spiking (in the form of individual spikes, spike trains or spike and wave features). These spikes are seen in the majority of epileptic patients, whereas only a very small number of nonepileptic patients show this feature. For this reason inter-ictal spike detection plays a large part in the diagnosis of epilepsy. However, during an isolated spike, the brain is not in a clinical seizure. A very different EEG pattern is seen during the ictal period consisting of rhythmic waveforms. Although inter-ictal spikes offer evidence of epilepsy this can only be confirmed and a complete diagnosis made, by an observed seizure. Hence detection of epilepsy is basically the problem of recognizing EEG spikes and classifying them as epileptic or normal.

This classification approach is not new. In fact, in the late 1960s there were a number of attempts at performing the automatic classification using the discriminant analysis techniques (3). However, this work was largely abandoned as most researchers concluded that classification based on discriminant techniques does not generalize well, i.e. while good results were used for data that was used to train the system, high accuracy was not achieved in classifying the unseen data that was not used in training.

Automated spike detection has been approached from different directions. This paper presents the current progress towards a system for automatically detecting epileptic seizures within EEG recordings using a LAMSTAR Neural Network (4).

Automatic analysis of the human EEG for assisting in the diagnosis of epilepsy started in the early 1970s. In 1973 Prior et al. (5) described a system which identified tonic-clonic seizures by detecting a large increase in EEG signal amplitude followed by a clear decrease, accompanied by high levels of muscle activity. Ives et al. applied amplitude discrimination to the sum of all 16 channels of EEG and was successful in detecting large seizures (6,7). Moving away from software
methods, Babb et al.\textsuperscript{1, 7} presented an electronic circuit to perform seizure detection. From these beginnings the analysis of epileptic EEG has progressed in two main directions: 1. Seizure detection; 2. Inter-ictal event detection.

Some recent work has also been done on automatic systems to locate the origin of focal seizures\textsuperscript{1}. Ambulatory EEG recording achieved widespread usage in the mid-1980s. Prior to this, most work in epileptic EEG analysis concentrated on the second detection of inter-ictal events. This bias was probably due to the fact that long-term monitoring would take place in a dedicated unit; in these conditions it is relatively easy to identify seizures when they occur. Ambulatory recording, however, introduces the need to scan large amounts of EEG data for seizures, a time-consuming operation.

In 1982, Gotman presented a computerized system designed to detect a variety of different types of seizure\textsuperscript{1, 8}. This method has been updated several times but remained basically unchanged over the 1980s\textsuperscript{1}. Interest in the issue of seizure detection has resurfaced during the 1990s with a number of papers published by different research groups. Of these, Weng and Khorasani employed ANN for that purpose, through with high false alarm rates\textsuperscript{1, 9}. Pradhan et al. used raw EEG directly with ANN\textsuperscript{1, 10}.

The work discussed in the present paper employs the LAMSTAR ANN for detection of seizures. LAMSTAR provides the flexibility to describe a given problem in form of different independent attributes, as shown in the next section. Each attribute enhances the chance of faultless detection of epileptic seizures. Relative spike amplitude of epileptic EEG and spike rhythmicity were chosen to be the two attributes to characterize epileptic seizures. However, the number of attributes could be increased with a more comprehensive training on LAMSTAR and subsequent faultless detection.

**NEURAL NETWORK IMPLEMENTATION**

**The LAMSTAR Neural Network**

The LAMSTAR (Large-Memory Storage and Retrieval) neural network was specifically developed for application to problems involving very large memory that relates to many different categories (attributes) where some data is exact while the other is 'fuzzy' and where for a given problem some categories might be totally missing. Consequently LAMSTAR has been widely used in numerous problems involving decisions, diagnosis and recognition\textsuperscript{1, 4}.

The LAMSTAR network attempts to imitate processes of the human brain and the central nervous system, concerning storage and retrieval of patterns, impressions and sensed observations, including the processes of forgetting and of recall. LAMSTAR does so efficiently by using Self Organising Map (SOM) modules combined with the statistical decision tools. Thus LAMSTAR is a collection of different types of neural networks which work in tandem to approximate the working of the human brain in gross manner.

The LAMSTAR employs standard perception-like neurons that are arranged into many SOM modules. Each SOM module has several neurons which compete among each other (within the SOM) on the 'winner takes all' philosophy. Each SOM module is responsible for learning one particular attribute of the problem at hand. Therefore several attributes describing the problem are presented to each different SOM module. The collection of all the attributes is called a 'word' whereas each individual attribute is referred as 'subword'. Thus training a LAMSTAR requires characterizing the given problem with a set of attributes and then subsequently training the LAMSTAR with each of these attributes. Once training is accomplished and a set of test attributes is presented to the LAMSTAR, each SOM module returns the best matching corresponding attribute and thus a final decision is made on the basis of combined response of all the SOM modules.

In contrast to most other ANNs, the LAMSTAR ANN continues to train also during normal operation without reprogramming or slowing down, to continuously learn from its mistakes, thus continuing to improve its performance. It also needs no reprogramming if for some data sets or patient, some attributes are missing. It is important to note that the LAMSTAR can use, as input sub-words, attributes other than those derived from the EEG signals themselves (such as patient history or other observations or tests, if available though the recent results are solely signal-based).

In the current design, the LAMSTAR is trained for two attributes that describe epilepsy; the epileptic spike amplitude and the epileptic spike occurrence frequency.

**Architecture of the LAMSTAR neural network**

The LAMSTAR network used for seizure detection is a much simpler version of what has been proposed by Graupe and Kordylewski\textsuperscript{11}. It consists of two SOM (Self Organising Maps) modules that were made to learn the two attributes of the epileptic EEG. Each SOM module

![Figure 1: Normal EEG. Note low amplitude random nature](image-url)

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![Figure 2: Epileptic EEG. Note high amplitude](image-url)
A given problem is described by several attributes derived from problem data.

Each attribute is used to train the LAMSTAR.

Given Problem

LAMSTAR
Network

Learn, Detect & Interpolate

Subwords

Figure 3: A logical description of LAMSTAR’s functionality

contained 10 neurons that competed with each other on 'winner takes all' concept. The LAMSTAR architecture employed for detecting epilepsy is as shown in Figure 4, while Figure 5 describes LAMSTAR’s application to the epilepsy detection problem.

PRE-PROCESSING

Procurings the EEG Signals

In order to train the LAMSTAR, real time EEG was procured. Two sets of EEG data files were selected. One set consisted of the time series of EEG from normal subjects during wakefulness with eyes open. The other set consisted of the time series of epileptic EEG that was recorded during the occurrence of epileptic seizures in subjects suffering from epilepsy. Each set contained 100 single channel EEG segments of 23.6 sec duration. These segments were selected and cut off from continuous multichannel EEG recordings after visual inspection for artifacts, e.g., due to muscle activity or eye movements. All EEG signals were recorded with the same 128-channel amplifier system, using an average common reference. After 12 bit analog-to-digital conversion, the data were written continuously onto the disk of a data acquisition computer system at a sampling rate of 173.61 Hz. The EEG was filtered using a band pass filter. Band-pass filter settings were 0.5340 Hz ~12 dB/ octave. Two exemplary records from this set are shown in Introduction.

Pre-processing the EEG signal

The most crucial step in training an ANN is pre-processing the input data. Pre-processing involves extracting the training attributes from the EEG. To train the LAMSTAR two attributes were chosen: relative spike amplitude and spike occurrence frequency. The following algorithm was used to extract the above mentioned attributes:

(a) Divide the EEG time series into small segments of duration 1 sec. EEG is considered to be stationary for an interval of 1 sec. Moreover segmentation into smaller blocks helps in analysis of local phenomena.

(b) To each segment apply a median filter of suitable length. The length of the filter should be chosen to smooth the epileptic spikes. Since spike duration is normally between 70 and 100 msec, a median filter over 15 msec was chosen for smoothing the spikes.

Subsequently, the median filtered signal is subtracted from the original EEG segment to yield a difference signal. The difference signal thus emphasizes epileptic spikes, if any are present in the original segment. When the original EEG segment is normal, only very low amplitude spikes would remain in the difference signal.

(c) Subsequently further enhance the epileptic spikes in the difference signal by applying some sort of nonlinearity (e.g. raising the difference signal by an odd power). This also reduces any noise effects.

(d) Further apply thresholding to the enhanced epileptic spikes. In the present study the threshold was 50% of the maximum spike amplitude in the segment. This demarcates the spikes from any leftover noise.

(e) Store the maximum spike amplitude and calculate the number of spikes in a particular segment.

(f) Quantize the spike amplitude and spike occurrence frequency of step (e). Both the variables were quantized into five bits each.

(g) Combine the quantized attributes to form a comprehensive word that would be fed to the LAMSTAR.

(h) Train the LAMSTAR using the word formed in step (g) above.

Figure 6A–C illustrate the various pre-processing steps prior to feeding the data into the LAMSTAR.

The peak occurrence frequency and maximum peak amplitude peak occurrence for a particular segment were quantized before feeding into the LAMSTAR. Quantization shortens the size of input words and subwords by coding the data in fewer bits. Also, it renders slightly dissimilar subwords similar, to decrease the number of training/testing patterns. For quantization.
The maximum epileptic spike amplitude was rounded to the nearest multiple of 100 and then divided by 100. Hence, a spike of 345 microvolt yields 3. Note that five bit binary coding of 345 is 00011. Spike occurrence frequency is not quantized since it is a small number. Also, errors in spike occurrence frequency greatly affect diagnosis (Table 1).

Therefore, for the top segment above, after quantization, the sub word becomes: 00011 (3); 00110 (6).

The above input word (2-subwords) characterizes one segment of EEG that was pre-processed. Since the segment that was considered belonged to an epileptic time series of EEG, the LAMSTAR would be trained to flag detection of epilepsy while being trained with the above word. The algorithm that is used to train the LAMSTAR to discriminate epileptic EEG from non-epileptic one is described in next section.

Figure 7A–C show several EEG time series segments, their corresponding training words and the subsequent target values. All amplitudes are in microvolts.

**Table 1: Signal quantization**

<table>
<thead>
<tr>
<th>Before quantization</th>
<th>After quantization</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum spike amplitude (in microvolt)</td>
<td>Spike Occurrence</td>
</tr>
<tr>
<td>345</td>
<td>6</td>
</tr>
</tbody>
</table>

**TRAINING OF THE NEURAL NETWORK**

The training of LAMSTAR network is a two stage process: The first stage involves the training the SOM module neurons in a particular SOM module, say $k$, to learn the $k$th sub word. The second stage is the training of the output neurons to recognize a particular outcome (diagnostic decision).

1. **Training of SOM module neurons** consists of the following steps:
   a. **Initialization:**
      Initialize the weights of each SOM module neuron with some random weights and normalize the weights. Also assign random weights to links between each SOM module neuron and the output layer neuron. Randomize these weights also.
   b. **Training of SOM Module neurons**:
      (i) For each input word presented to the LAMSTAR network, input the $k$th sub-word to the $k$th SOM module.
      (ii) Present the $k$th sub-word to each neuron in the $k$th SOM module.
      (iii) Calculate the total activation of each neuron in the $k$th SOM module and select the neuron with the highest total activation. Declare the neuron with the highest value of total activation as the winner of the $k$th SOM module for $k$th sub-word. Thus each SOM module will have a winner for the sub-word that is presented to that SOM module.

2. **Training of output neurons**:
   For every output neuron, calculate the sum of all link weights that connect it to the winning neurons in each SOM module. Denote this sum (i), where (i) is a particular output module's neuron. Subse-
Diagnosis Results

The LAMSTAR was trained by 500 words that were created as shown above. The EEG segments used to train the network were collected from different subjects. Once the LAMSTAR had been appropriately trained with a large number of training patterns, it was tested with test patterns. The test patterns were created in the same way as the training patterns as described above segmenting epileptic and non-epileptic EEG that was not used for training. The test patterns for epilepsy were sourced from various patients.

The overall success percentage of the algorithm, when tested over 750 segments of epileptic as well as non-epileptic EEG, was 98.1%, which corresponds to a 1.6% miss rate (namely, when an epileptic EEG segment was diagnosed as nonepileptic). However if the robustness of the algorithm is measured in terms of gross errors that takes into account the 'misses' as well as the 'false alarms', the overall accuracy of the network is 97.2%.

EEG segments that were accurately detected by the LAMSTAR are as in Figure 7A,B, (c) above. The case of Figure 8 is however one of the 1.6% where the LAMSTAR's decision was wrong, resulting in a 'miss'.

Note that in the segment of Figure 8, there are several peaks with amplitude between 50 to 100 microvolts. Though the amplitude is low, the peak occurrence frequency is high and that made LAMSTAR give wrong result. However this error was easily corrected by training LAMSTAR with several normal EEG segments that had several peaks of low amplitude that were non-pathological.

Conclusion

The LAMSTAR network was able to detect epilepsy with an accuracy of 98.4%, namely, a 1.6% miss-rate, or a 97.2% overall accuracy if false alarms are also considered (in addition to the 'misses'). Characterization of epilepsy by two attributes, epileptic spike amplitude and spike occurrence frequency, thus produced commendable results using LAMSTAR. However this would come at the cost of lots of pre-processing that would undermine the fast, automated decision making cap-
ability of the ANN. Wavelets could be effectively used to track the epileptic patterns over certain scales.

Further improvement in performance can be achieved by adding sub-words to the LAMSTAR, that are based on patient data, even fuzzy (including patient history and general physician observations, beyond EEG data). Another factor that can improve the performance of the network substantially and make epilepsy detection most robust is the use of the correlation links. Since in the current study only two attributes were used, the implementation of correlation links was omitted. However as the number of attributes describing a problem increase, correlation links become essential to the design of the network. Strong correlation between related attributes forms the basis of LAMSTAR's detection capability. For example strong correlation links between large spike occurrence frequency and small inter-spike interval gives a good indication of epilepsy. All these are easily incorporated into the LAMSTAR, while causing difficulty to other ANNs, such as Backpropagation, especially if not all attributes are available for all patients considered. In that case, the LAMSTAR is unique in its ability to perform in the face of missing data attributes.

The pre-processing (via median filtering, nonlinear operator and thresholding, as used in this design) allows very considerable immunity to noise or to artifacts.

An extension of the present LAMSTAR-NN/nonlinear filtering approach by applying it to 3-D epilepsy source-detection via the EEG (EEG inverse problem) should also be considered.

REFERENCES
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