Reinforcement Learning based on Seizure Detection

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I. Abstract

The electroencephalogram (EEG) signals are commonly used for diagnosis of epilepsy. In this paper we present a method of electroencephalogram (EEG) signal classification using a reinforcement learning model. It is known that ictal(seizure) EEG signals have higher energy compared to non-ictal(seizure-free). So, these two parametres ictal and non-ictal, are given as inputs to train our model for classification using the Deep Reinforcement Learning approach. Initially we perform 6th order low pass Butterworth filter having a sampling frequency of 45.12 Hz for preprocessing our data then after extracting the 92 features from our preprocessed data and reducing it into a single feature using Dimensionality Reduction Technique. After feature extraction we perform the classification action on a sample at each time step and our model evaluates the classification action and returns a reward to the agent .For each good action agent will be awarded and will be punished for every bad action, try to gain maximum reward as sequential decision making process by applying Deep Q Network (DQN) algorithm. Now our trained mode can predict a set of eeg signals from seizure and seizure-free category. Children Hospital Boston, Massachusetts Institute of Technology (CHB-MIT) and Bonn Datasets are two publicly available datasets used in this project.

II. Keywords

Butterworth filter, Dimensionality Reduction Technique, time series, Reinforcement learning, Deep Q-Network(DQN)

III. Introduction

The word epilepsy originates from the Latin and Greek word ‘epilepsia’; which means ‘seizure’ or ‘to seize upon’. It is a neurological disorder with unique characteristics, tending of recurrent seizures. The context of epilepsy. Found in the Babylonian text on medicine, it was written over 3000 years ago. This disease is not limited to human beings,but extends to cover all species does not give any type of clues about the cause of or severity of the seizures. It is remarkable and uniformly distributed around the world.
Reinforcement learning algorithms enable an agent to learn an optimal behavior when letting it interact with some unknown environment and learn from its obtained rewards. An RL agent uses a policy to control its behavior, where the policy is a mapping from obtained inputs to actions. Reinforcement learning is quite different from supervised learning where an input is mapped to a desired output by using a dataset of labeled training instances. One of the main differences is that the RL agent is never told the optimal action, instead it receives an evaluation signal indicating the goodness of the selected action.

In this paper we have presented a method of electroencephalogram (EEG) signal classification using a reinforcement learning (RL) model. So, there are two parametres ictal and non-ictal, that are given as inputs to train our model for classification using the Deep Reinforcement Learning approach. Firstly we have performed a 6th order low pass Butterworth filter having a sampling frequency of 45.12 Hz for preprocessing our data then after extracting the 92 features from our preprocessed data and reducing it into a single feature using Dimensionality Reduction Technique. For each correct action, the model will be awarded with a positive number and with a negative number for wrong answer. Model will try to get maximum positive reward by applying the Deep Q Network algorithm.

IV. Main Contribution

In this paper, we mainly focus on preprocessing and feature extraction by applying a sixth order low pass Butterworth filter with normalized cutoff frequency of 45.12 Hz in our time series data for reducing the noise such as power line interference, muscle movement and eye blinking for preprocessing. Then applying Linear Discriminant Analysis algorithms using Dimensionality Reduction Technique for extracting the features transform the data from a high-dimensional space into a low-dimensional space so that the low-dimensional representation retains some meaningful properties of the original data.

V. Experimental Datasets/Dataset & Baseline Methods

A. *Experimental Datasets*

We used two publicly available datasets for the experiment, CHB -MIT and Bonn dataset

CHB-MIT: CHB-MIT Dataset, collected at the Children's Hospital Boston, consists of EEG recordings from pediatric subjects with intractable seizures. Subjects were monitored for up to several days following withdrawal of anti-seizure medication in order to characterize their seizures and assess their candidacy for surgical intervention.

Recordings,grouped into 23 cases,were collected from 23 subjects (5 males,ages 3-22;and 17 females,ages 1.5-19).The file named Subject-Info contains the gender and age of each subject.(Case chb24 was added to this collection in December 2010,and is not currently included in SUBJECT-INFO.)

Each case (chb01,chb02,etc) contains between 9 and 42 continuous .edf files from a single subject. Hardware limitations resulted in gaps between consecutively-numbered .edf files ,during which signals were not recorded;in most cases,the gaps are 10 seconds or less,but occasionally there are much longer gaps. In order to protect the privacy of the subjects, all protected health information(PHI) in original .edf files has been replaced with surrogate information in the files provided here.Dates in the original .edf files have been replaced by surrogate dates,but the time relationship between individual files belonging to each case have been preserved.In most cases,the .edf files contains exactly one hour of digitized EEG signals,although those belongings to case chb10 are two hours long,and those belongings to cases chb04,chb06,chb07,chb09,and chb23 are four hours long;occasionally, files in which seizures are recorded are shorter.

All signals were sampled at 256 samples per second with 16-bit resolution.Most files contain 23 EEG signals(24 or 26 in a few cases). The international 10-20 system of EEG electrode positions and nomenclature was used for these recordings.In a few seconds,other signals are recorded,such as an EEG signal in the last 36 files belonging to case chb04 and a vagal nerve stimulus(VNS) signal in the last 18 files belonging to case chb09.In some cases,up to 5 “dummy” signals were interspersed among EEG signals to obtain an easy to read display format;these dummy signals can be ignored.

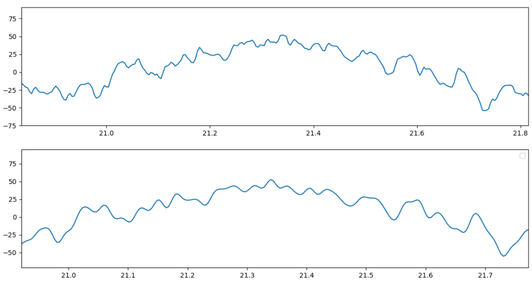
The file RECORDS contains a list of all 64 .edf files included in this collection ,and the file RECORDS-WITH-SEIZURES lists the 129 of those files that contain one or more seizures.In all , the records include 198 seizures(182 in the original set of 23 cases); the beginning ([) and the end (]) of each seizure is annotated in the .seizure annotation files that accompany each of the file listed in RECORDS-WITH-SEIZURES.In addition,the files named cnn-summary.txt contain information about the montage used for each recording, and the elapsed time in seconds from beginning of each .edf file to beginning and end of each seizure contained in it.

Bonn-Dataset: Our seizure recognition experiments are conducted using a widely used and publicly available EEG database produced by Bonn university. This database consists of five diverse subsets (set A-E) denoted as Z,O,N,F and S.Sets A and B are composed of surface EEG recordings of healthy volunteers in wakeful state with eyes open and eyes closed, respectively. On the other hand,Sets C,D and E are gathered from patients with epilepsy. There ,Sets C and D were recorded from hippocampal formation of the opposite hemisphere of the brain. Set D was recorded from within the epileptogenic zone.Set E only included seizure activities. Each of these sets contains 100 single-channel recordings of EEG signals with a sampling rate of 173.61 Hz and a duration of 23.6 s. The corresponding time-series is sampled into 4097 data points.Besides, the Rochester Institute of Technology divided every 4097 data points into 23 chunks. Each chunk contains 178 data points for 1 second.To increase the number of samples for training a deep model ,Bonn Dataset in this format is adopted , whose amount of sample increases 22 times.Therefore ,the number of each category has 2300 EEG samples.

B. Dataset & Baseline Methods

In the CHB-MIT dataset ,we extract the region of interest from the recordings or the incident when seizure actually happens in the 71 text files and same for non-seizure.After extraction we conclude 1136640/256 = 4440 sec or 74 min recordings of seizure and same 74 min of non-seizure data for all the 23 patients.

Now for preprocessing, we apply a sixth order low pass butterworth filter with cut off frequency of 45.12 Hz.Our filter will pass only the frequencies having less than cutoff frequency and remove all the frequencies higher than cut off frequency.Here we have shown the figure below where we can clearly see that original signal have been smoothed after applying low pass filter.



Then after, we perform the feature extraction so there are 23 channels in our dataset and recording of 74 *2 = 148 min (8880 sec) for both seizure and non-seizure patients. for each channel, we mainly calculate four features: **variance, standard deviation ,Shannon entropy and kurtosis**.Total 23*4 =92 features will be created for segment of every 10 sec (10*256 = 2560) signal. So 1136640/2560 = 444 rows will be created for 92 features for seizure data. After creating 444*92 matix for seizure and 444*92 for non*seizure, we perform linear discriminant analysis for reducing the 92 features into single features because more input features often make a predictive modelling task more challenging to model, more generally referred to as the curse of dimensionality.

finally features are extracted and Now our agent is ready for training.Here we train our model using Deep Q Network, a standard Deep Reinforcement learning algorithm, a neural network, uses loss function and the predicted (current) Q value, Target Q value, and Observed reward to complete the loss to train the network and thus improve its the predictions.

VI. Proposed Approach

"Reinforcement learning is a type of machine learning method where an intelligent agent (computer program) interacts with the environment and learns to act within that." How a Robotics dog learns the movement of his arms is an example of a reinforcement learning Agent learns to behave in an environment by performing the actions and seeing the results of actions. For each good action, the agent gets the reward positive feedback, and for each bad action, the agent gets negative feedback or penalty. It is a core part of Artificial Intelligence, and all AI agents work on the concept of reinforcement learning.Here we do not need to pre-program the agent, as it learns from its own experience without any human intervention.

Now we discuss the Deep Reinforcement Learning (DRL) approach which we are going to use in our model which is a combination of deep learning and reinforcement learning. In DRL, value and policy can be expressed by a neural network, which allows it to deal with a continuous state or action. In recent years, deep reinforcement learning has been successfully applied to computer games, robots controlling. Here, a deep reinforcement learning approach is used for eliminating noisy data and learning better features, which made a great improvement in classification performance.

Now we perform classification tasks using deep Q learning (DQN). Assume that the training data set is $D = \{(x_1, l_1), (x_2, l_2)\ldots\ldots\ldots (x_T, l_T)\}$ where x_i is the ith sample and l_1 is the label of the ith sample. We propose to train a classifier as an agent where

State S: The state of environment is determined by the training sample. At the beginning of training, the agent receives the first sample x1 as its initial state s1. The state of the environment at each time step corresponds to the sample xt. When the new episode begins, the environment shuffles the order of samples in the training data set.

Action A: The action of the agent is associated with the label of the training data set. The action taken by the agent is to predict a class label. For binary classification problems, A = {0, 1} where 0 represents the non-ictal(seizure-free) and 1 represents the ictal(seizure) class.

Reward R: A reward rt is the feedback from the environment by which we measure the success or failure of an agent's actions. In order to guide the agent to learn the optimal classification policy in the data, the absolute reward value of the sample in the ictal and non-ictal are the same .

Discount factor γ: γ ∈ [0, 1] is to balance the immediate and future reward.

Episode: Episode in reinforcement learning is a transition trajectory from the initial state to the terminal state {s1, a1, r1, s2, a2, r2, ..., st, at, rt}. An episode ends when all samples in the training data set are classified or when the agent misclassified the sample from the class. •

Policy πθ: The policy πθ is a mapping function π : S → A where πθ(st) denotes the action performed by an agent in state st. The policy πθ can be considered as a classifier with the parameter θ. With the definitions and notations above, the proposed classification problem is formally defined as to find an optimal classification policy π ∗ : S → A, which maximized the cumulative rewards.

VII. Algorithm:

Training

Input: Training data $D = \{(x_1, l_1), (x_2, l_2)\ldots\ldots\ldots (x_T, l_T)\}$

Episode number K

Initialize experience replay memory M

Randomly initialize parameters θ

Initialize simulation environment ε

for $episode\ k = 1\ to\ k$ **do**

Shuffle the training data D

Initialize state $s_1 = x_1$

for $t = 1$ *to* T **do**

Choose an action based ε-greedy policy:

$a_t = \pi_\theta(s_t)$

$r_t, terminal_t = STEP(a_t, l_t)$

Set $s_{t+1} = x_{t+1}$

Store $(s_t, a_t, r_t, s_{t+1}, terminal_t)$ to M

Randomly sample $(s_j, a_j, r_j, s_{j+1}, terminal_j)$ from M

if $target_j = True$:

Set $y_j = r_j$

else $target_j = False$:

Set $y_j = r_j + \gamma\, max_{a'}\, Q(s_{j+1}, a'\,; \theta)$,

perform a gradient descent step on $L(\theta)$ w.r.t.θ:

$L(\theta) = (y_j - Q(s_j, a_j; \theta))^2$

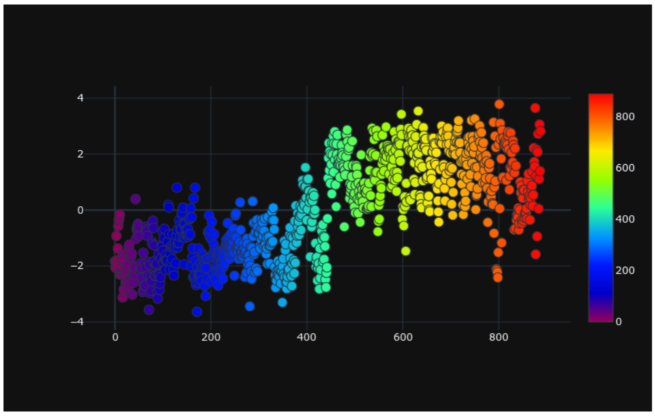
if $terminal_t = True$ **then**

break

We construct our model using Deep Q-Network and the architecture of the Q network depends on the complexity and amount of training data set. The input of the Q network is consistent with the structure of the training sample, and the number of outputs is equal to the number of sample categories. In fact, the Q network is a neural network classifier without the final softmax layer. The training process of Q network is described in Algorithm In an episode, the agent uses the -greedy policy to pick the action, and then obtains the reward from the environment through the STEP function. The deep Q-learning algorithm will be running about 1500 iterations (updates of network parameters θ). We save the parameters of the converged Q network which plus a softmax layer can be regarded as a neural network classifier trained by data.

VIII. Result & Discussion

Here we predict our model using both Machine learning and Reinforcement Learning and achieve 92% and 94.8% accuracy respectively.



We successfully classify our model, In our experiment, to evaluate the classification performance in the data sets more reasonably,

Reinforcement Learning model

Train accuracy: 0.9017713365539453

Train:

True Negatives = 285, False positive = 31, False negative 30, True Positive = 275

Test accuracy 0.9400749063670412

True Negatives = 124, False positive = 4, False negative = 12 , True Positive = 127

n =888	**Predicated :NO**	**Predicated:YES**
Actual: NO	285	31
Actual:YES	30	275

n =888	**Predicated :NO**	**Predicated :YES**	
Actual:NO	TN =285	FP =31	316
Actual:YES	FN =30	TP =275	305
	315	306	

VIII. COMPARISON

In this section, we show a comparison table to understand the advantages of the proposed approach in the seizure detection task. Performance of the proposed RGB feature based transfer learning approach has been estimated by varying the pre-trained network and the number of epochs, keeping the learning rate constant. Table-2 represents a summary of the complete experiment conducted using mentioned pre-trained networks to classify seizure and without seizure EEG signals through proposed approach. In Table, we mentioned estimated classification accuracy of the proposed approach as well as for implemented SVM and ANN classification techniques over the same data.

Classifier(s)	**Accuracy (%)**	**Dataset**	**Authors**
SVM	93.8	CHB-MIT	Shoeb and Guttag
ANN	96.4	BONN	Guo et al.
Random forest	93.8	EPILEPSIAE	Donos et al.
Logistic Regression	92	CHB-MIT	Our Project
Reinforcement Learning	94	CHB-MIT	Our Project

Several approaches have been in literature of seizure detection using University of Bonn EEG data.

In the table, a comparison between the proposed and existing approaches has been shown. It shows the proposed approach achieved higher accuracy than the mentioned existing approaches over the same dataset. Hence, the proposed approach can be one of possible approaches for the seizure detection over the small EEG dataset.

IX. FUTURE SCOPE

Overall, it is believed that the brain solves problems through reinforcement learning and neural networks organized as hierarchical processing systems. The field of AI has been trying to adopt and implement this strategy in computers, notable progress has been seen recently due to better understanding about learning systems, decline of computing costs, and increase of computational power and the seamless integration of different technologies and technical breakthroughs. There are still some situations where these methods fail, underperform against traditional methods and therefore must be improved.

For example the shortcomings of the current techniques and existing open research challenges, and speculate about some future perspectives that will facilitate further development and advancement of the field.

The combined computational capability and flexibility provided by the two prominent ML methods (i.e. DL and RL) also have limitations. Both these methods require heavy computing power and memory, and hence are not worthy of being applied to moderate size data sets. Representing action-value pairs in RL is not possible to use all nonlinear approximators which may cause instability or even divergence in some cases. Also bootstrapping makes many of the RL algorithms hard and inapplicable to real-time application, as they are too slow to converge and in some cases too dangerous(e.g. autonomous driving).. Very few existing techniques support harnessing the potential power of distributed and parallel combination through cloud computing.

The problems pertaining to observability of RL are yet to be completely solved, and optimal action selection is still a huge challenge. But there are timely opportunities to employ deep RL in biological data mining, for example, deriving dynamic information from biological data coming from multiple levels to reduce data redundancy and discover novel biomarkers for disease detection and prevention. Also, new unsupervised learning for deep RL methods is required to shrink the necessity of large sets of labeled data at the training phase.

X. CONCLUSION

This paper introduces a novel model for classification of seizure(ictal) and non-seizure or seizure free patients using deep reinforcement learning over logistic regression and ANN. The model explians the classification problem as a sequential decision making process.We use mainly deep Q learning algorithms to find the optimal classification policy for sequential decision making process and theoretically analyze the impact of the specific reward function of Q network during the training.

After feature extraction we perform the classification action on a sample at each time step and our model evaluates the classification action and returns a reward to the agent .For each good action agent will be awarded and will be punished for every bad action, try to gain maximum reward as sequential decision making process by applying Deep Q Network (DQN) algorithm.

The results are assessed and deployed when sufficient accuracy is reached. The results depicted that the accuracy is above 94%. Results from other pre-trained networks are also evaluated. Future research can be conducted to test the results by varying the learning rate and other parameters. Extensive work can be performed using other efficient pre-trained networks to improve the capability of transfer learning efficiency.

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