Application of deep learning to seizure classification

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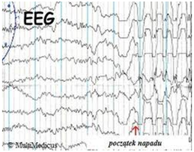
Introduction

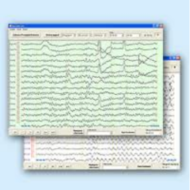
- The number of people suffering from epilepsy - 50 million people worldwide,
- Approximately 1-2% of the population has seizures,
- The number of patients with epilepsy in Poland - 300-400 thousand,
- Seizure detection is difficult because of artifacts (disturbances in the bioelectrical activity of the brain, e.g. eye movement),
- An epileptic seizure can occur at any age, and its causes are, for the most part, unknown,

Electroencephalography (EEG)

- A non-invasive diagnostic method to study the bioelectrical activity of the brain,
- EEG test - appropriate placement of electrodes on the head recording changes in electric potential on the skin surface,
- EEG tests are performed for monitoring and diagnostic purposes, e.g. epilepsy, sleep disorders, in the diagnosis of coma and brain death, organic brain diseases.







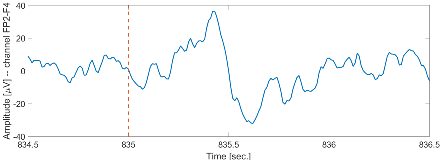
Detection of epileptic seizures

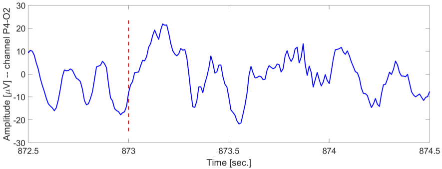
- The EEG recording taken during an epileptic seizure contains the most useful information,

  Problem: such situations are observed in a relatively small number of patients (only about 30%)

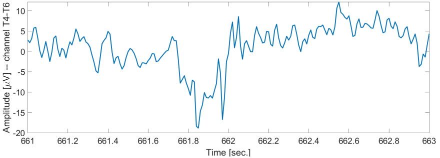
- Inter-ictal EEG recording - taken between epileptic seizures,
- These graphoelements are - correlated with epileptic seizures,
- They have the form of the so-called sharp wave or spike followed by a slow wave,
- Detection of epilepsy in 30% - 70% of cases.

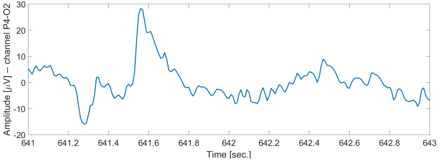
- Spike duration - from 30 to 70 ms,
- Slow wave duration - from 70 to 100 ms,
- Spike-slow wave complex usually lasts about 250 ms,
- They can also occur as spike-slow wave complexes,
- Further in the presentation, such seizures are called short-term,
- Due to the correlation of inter-ictal seizures with epilepsy, they will be called epileptic seizures.





Examples of short-term epileptic seizures.





Examples of correct EEG affected by artifacts.

- **Problem:** the quality of diagnosis is greatly influenced by the so-called artifacts,
- Artifacts are EEG signal disturbances caused by:
  - technical reasons - voltage fluctuations,
  - biological causes - muscle tightening, eye movement, body movement,
- Detection of epileptic seizures in the EEG inter-epileptic record - a difficult problem to solve.

Solution overview

- **Visual inspection** - EEG review by a neurologist specialist,

  Disadvantages: Time-consuming; the same record may be interpreted differently by different specialists,

- **Parametric description of graphoelements** – Characteristic graphoelement can be described by parameters, e.g. duration, slope, surface area of a part with negative and positive values,

  Disadvantages: Difficulty in the automatic description of a graphite element, often with an unusual course,

- **Statistical analysis** - Detection of irregularities based on the analysis of statistical parameters of the course,

  Disadvantages: Significant influence of artifacts on the quality of seizure detection.

- **Frequency methods** - Analysis of EEG signals in the frequency domain gives a lot of valuable information; methods of representing EEG signals in the time-frequency domain are of particular importance,

  Disadvantages: High computational complexity with a large number of channels and long time sequences,

- **Classification** - Detection of epileptic seizures comes down to the problem of classification (normal status / seizure),

  Disadvantages: Determining the appropriate set of attributes representing the EEG image.

Database of EEG records

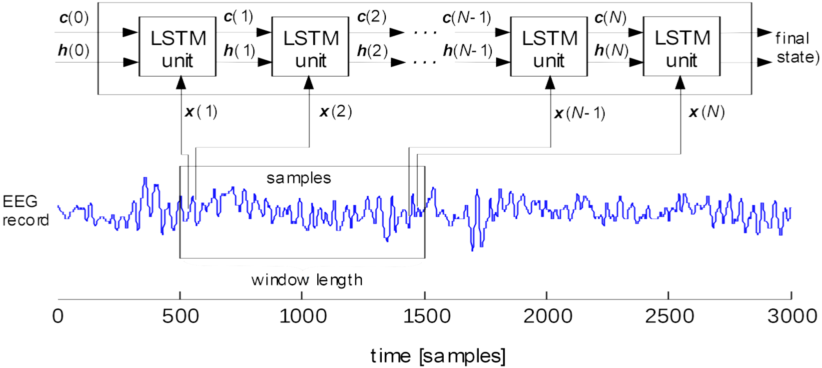
- The data was made available by the doctors of the Neurology Department of the University Hospital in Zielona Góra, Poland,
- Each record contains a record lasting from several to several dozen minutes, downloaded in 16 measurement channels,
- Data set containing 1176 EEG records including 588 epileptic and 588 healthy cases was split into the training and testing sets,
- The database contains records collected from patients with diagnosed epilepsy (104 records) as well as for healthy people (71 records),
- For each case, the database contains a specialist's decision specifying the characteristics of a given record.

Application of deep learning

- Each EEG record should be given an appropriate output representation:
  1. Heteroassociation - each input time sequence of n is assigned an output sequence of n length, the values of which determine the patient's condition at a given moment in time,
  2. Classification - each time sequence of n is assigned a number defined by the label " epileptic seizure "/" normal state ",
- The neurologist gave estimated times of the seizure,
- The end time of the seizure is unknown (also the length of the time sequence representing the seizure is unknown),

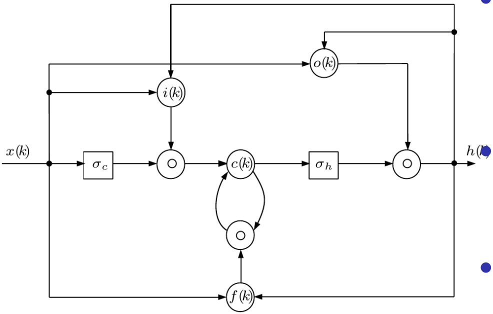
Proposal: Implementation of a detection system using a deep version of the LSTM network (Long Short-Term Memory).

The idea of processing using the LSTM network



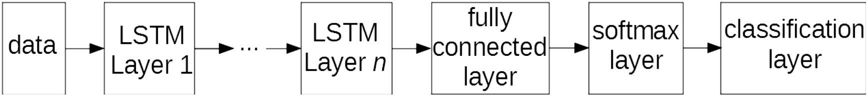
- LSTM has a short-term memory that lasts for a long time - the ability to analyze the signal in the time domain to determine where epileptic disorders occur,
- Processing of input sequences and simultaneous storage of long-term relationships between samples.

LSTM processing unit



- The LSTM processing unit consists of a memory cell, an input gate, an output gate and the forget gate,
- A memory cell is responsible for storing data for an arbitrary period of time,
- Gateways ensure data flow (communication) in the neural model.

Structure of a deep LSTM network



- **LSTM layers** - process input sequences extracting and remembering long-term relationships between samples,
- **Full connection layer** - sends LSTM processing results to the next layer,
- **Softmax layer** - assigns the probability of assigning a given sequence to the appropriate class,
- **Classifying layer** - assigns a label to the input sequence using the cross entropy function.

Classification quality evaluation

- a sensitivity (a true positive rate) tpr – for measuring the rate of correctly identified seizures,
- a specificity (a true negative rate) tnr – for measuring the rate of correctly detected healthy cases,
- a total accuracy acc – for measuring an overall quality of seizure detection.

Sequence-to-label deep LSTM network

- Input space - 16 sequences (16 measurement channels),
- Number of outputs 1 (label *healthy/seizure*),
- Data set containing 588 epileptic samples and 588 samples acquired from healthy subjects was enriched with 1040 samples acquired from epileptic subjects but marked as the normal operation,
- Division of data into training and testing set - repeated hold-out method with a coefficient of 0.5,
- Length of processed sequences - 1 seconds,

Investigated network structures.

network	number of nodes			
	1st layer	2nd layer	3rd layer	4th layer
net1	100	–	–	–
net2	50	50	–	–
net3	50	100	–	–
net4	100	70	–	–
net5	10	30	50	–
net6	50	30	10	–
net7	50	50	50	–
net8	50	100	150	–
net9	100	70	40	–
net10	50	50	50	50
net11	70	60	50	50

- Various LSTM structures containing from 1 to 4 LSTM layers and a different number of neurons in the layers were tested,
- Each network configuration was trained 5 times with the ADAM algorithm,
- Selecting the best network - the structure with the smallest number of parameters, which has obtained the acceptable values of the classification quality criteria,
- The best averaged results were achieved for the model **net 5**: ($tpr = 76\%$ and $acc = 88.3\%$).
- The highest values of tpr and acc were observed for the model **net 7**: $tpr = 79.8\%$ and $acc = 89.8\%$
- The model **net 7** was selected for further experiments.

Entire EEG record analysis

- An analysis of the full record (lasting several minutes on average) was performed with the use of a sliding window with a length of 1 seconds,
- Cut out sequences were classified online by the developed system,
- Thus, 104 EEG records for epileptic patients and 71 EEG traces from healthy individuals were analyzed,
- Each sequence was evaluated using indexes tpr, tnr and acc,
- For healthy subjects only the acc index was calculated (no real epileptic seizures).

Patients with epilepsy

- **In every case the epilepsy was diagnosed with tpr reaching the value from 20% to 100%.**
- For 33 patients the system detected all seizures pointed out by a neurologist ($tpr = 100\%$).
- In turn, the **specifity** index took the values from **27.7% to 100%** – in some cases the system generated a large number of false alarms about seizures.
- the overall accuracy was from the interval **28.2%-99.9%**.

Healthy subjects

- The total **accuracy** took the values from the interval **[68%,100%]**.
- In case of **66** examined subjects acc was greater than **90%**.

Dropout technique

- Improving the generalization of the best performing classifier **net 7**.
- The probability of dropout was set to $p = 0.2$.

model	epileptic patients			healthy subjects
	tpr	tnr	acc	acc
net 7	**78.7**	80.5	80.5	94.7
net 7 with dropout	**78.7**	**84.1**	**84.1**	**95.4**

Conclusions

- The choice of LSTM networks is justified due to their structure allowing implementation of long-term memory.
- Deep LSTM networks are able to extract characteristic relationships between signal samples representing different levels of abstraction.
- Analyzing the obtained results, we can conclude that the proposed approaches work quite well.
- Although the sequence-to-label model works a little better in classifying healthy cases, the results obtained for sick cases also return very good results and can be an alternative to imprecise methods of visual inspection.

Thank you very much for attention!!!