Lappeenranta University of Technology
LUT School of Engineering Science
Degree Programme in Computational Engineering and Physics
Intelligent Computing Major

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DETECTION OF EPILEPSY WITH A COMMERCIAL EEG HEADBAND

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ABSTRACT

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Detection of Epilepsy with a Commercial EEG Headband

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Epilepsy is a chronic brain disorder, characterized by reoccurring seizures. Automatic seizure detector, incorporated into a mobile closed-loop system, can improve the quality of life for the people with epilepsy. Commercial EEG headbands, such as Emotiv Epoc, have a potential to be used as the data acquisition devices for such a system. In order to estimate that potential, epileptic EEG signals from the commercial devices were emulated in this work based on the EEG data from a clinical dataset. The emulated characteristics include the referencing scheme, the set of electrodes used, the sampling rate, the sample resolution and the noise level. Performance of the existing algorithm for detection of epileptic seizures, developed in the context of clinical data, has been evaluated on the emulated commercial data. The results show, that after the transformation of the data towards the characteristics of Emotiv Epoc, the detection capabilities of the algorithm are mostly preserved. The ranges of acceptable changes in the signal parameters are also estimated.

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LIST OF SYMBOLS AND ABBREVIATIONS

ECG	Electrocardiography
ECoG	Electrocorticography
EEG	Electroencephalogram, Electroencephalography
FA	False Alarm
FFT	Fast Fourier Transform
FIR	Finite Impulse Response
iEEG	Intracranial EEG
ROC	Receiver Operating Characteristic
SD	Standard Deviation
SUDEP	Sudden Unexpected Death in Epilepsy
SVM	Support Vector Machine
VNS	Vagus Nerve Stimulation

1 INTRODUCTION

1.1 Background

Epilepsy is a chronic brain disorder, characterized by reoccurring seizures. The seizures are caused by the hyper-synchronous activity of the neurons of the brain. The unpredictable nature of the seizures lowers the quality of life due to the risks of harm [1], [2].

Automatic detection of epileptic seizures might be beneficial in two ways. In the diagnostic sense, it would allow to gain the data on seizure occurrences with higher accuracy. In the therapeutic sense, it might help to avoid or reduce the danger, caused by the seizures [3].

One of the most reliable measurements for epilepsy detection is EEG (Electroencephalogram). It directly maps the electrical activity of the neurons of the brain. Thus, it is providing the representation of the primary parameters, connected to the epileptic seizures [1].

The detector of epileptic seizures can be incorporated into a mobile closed-loop system for the everyday usage. Such a system would be performing continuous analysis of the input patient data. If the danger of seizure would be detected, warnings could be given to the patient and alarms could be sent to the patient's doctor and relatives. It might be even possible to perform various kinds of treatments or neurofeedback practices [2], [4], [5].

In order to utilize EEG in such a mobile system, specific mobile equipment would be needed for acquisition of the EEG signals. One option is to use commercial EEG headbands, such as Emotiv Epoc [6]. Usage of these headbands could make the technical process of the system development easier, as no need for the development of new equipment would be needed.

However, commercial EEG headbands differ from the clinical EEG equipment in various characteristics. The characteristics include referencing scheme, electrode locations, sampling rate and sample resolution. Moreover, additional noise might occur due to the differences in electrode contacts and the environment of usage. Such differences may affect detection performance of the existing algorithms.

To the best of author's knowledge, most of the research has been focused on the development of epilepsy detection algorithms based on the data, acquired in the clinical setting with clinical equipment. No databases of epileptic EEG signals from commercial headbands seem to exist. In order to incorporate the headbands in the real closed-loop system for everyday life, medical testing with their usage should be conducted. The effects of switching from the clinical equipment to the commercial should be studied and the corresponding data should be collected. Such experiments require considerable organizational effort and funding.

This work aims to estimate the impact of the changes of different characteristics of equipment for EEG acquisition on the performance of detection of epileptic seizures. For this estimation, the emulation of signals from commercial EEG headbands is performed by modifying clinical EEG data in appropriate ways. Such an estimate should prove the feasibility of usage of commercial EEG headbands for the purposes of epilepsy detection and help with decision-making, regarding the continuation of the research. In addition, this proof of concept can also help in bringing investments into further research.

1.2 Goals and delimitations

1.2.1 Objectives of the research

The objectives of this research arise from the aims to estimate the potential to use commercial EEG headbands in context of the detection of epileptic seizures. These objectives are to perform an emulation of epileptic EEG signals of a commercial EEG headband and to estimate the change in the epilepsy detection after each emulation step. The emulation is based on the existing clinical epileptic EEG dataset. The emulation steps involve changing the referencing scheme, reducing the sampling rate and the sample resolution, and adding noise. Performance evaluation is conducted with the utilization of the existing epilepsy detection algorithm.

Two experiments have been conducted in this research. The first one compares impacts of different emulation steps on the detection performance. The parameters of those emulations are taken so that the characteristics of signals reach the characteristics of Emotiv Epoc [6]. This experiment should demonstrate the relative importance of different characteristics of the devices.

The second experiment estimates the effects of varying parameters of each emulation step. For each emulation step, all the characteristics are fixed and only the parameters of that step are changed. This kind of experiment might show the extent, to which the parameters could be changed in the equipment for EEG acquisition.

1.2.2 Hypotheses

The main hypothesis of the research is that the EEG properties, related to epileptic seizures, would be preserved in the signals from commercial EEG-headbands. In addition, the emulation is assumed to be able to estimate the changes in the epilepsy detection performance by the algorithms when the clinical equipment is switched to the commercial EEG devices.

1.2.3 Restrictions

This research is performing only a subset of possible emulations. Some of the parameters can give different effects when changed in the physical system. Moreover, additional effects might occur due to the change in the environment of data acquisition.

Only one detector of epileptic seizures is considered in this research. Some of the effects of the detection performance change might be caused by the specifics of the algorithm and its implementations. Other detectors might behave differently and their performance on different emulated data should be studied.

The research does not guarantee the same behavior of the system, when the physical acquisition equipment is changed. It only gives an estimate, prediction of the effects that might occur. These predictions aim to motivate further research with real epileptic EEG signals from commercial EEG headbands.

1.3 Structure of the thesis

The rest of the report is organized as follows. In Section 2 an overview of the previous research in the field of epilepsy detection is given. The utilization of EEG signals for that purpose is also reviewed. The potential of the usage of commercial EEG headbands is also discussed in that section.

Section 3 explains the details of the detector of epileptic seizures, utilized in this research. The discussion overviews the general detection problem; mentions the features, extracted from the data; considers the classifier chosen to perform the detection; and describes the means to evaluate the detection performance.

Routines for the emulation of EEG signals from commercial headbands are described in Section 4. First, the motivation for the emulation is explained and is followed by the description of the original clinical data used as the basis in emulations. Next, the details of different emulation steps are given. They include respectively changing of the referencing scheme, selection of the subset of electrodes, changing the sampling rate and sample resolution, and finally addition of the noise.

Section 5 is devoted to the conducted experiments and their results. The section starts with the description of the two types of experiments. Then the results are given: first for the experiment, estimating the sensitivity of performance of the detector to the different emulation steps (i.e. different characteristics changed), continuing with those of the experiment, considering the sensitivity to the parameters of each emulation.

In Section 6, the results are analyzed and an attempt of explaining them is given. The suggestions for the future work are also made. Section 7 summarizes the work and concludes the achieved results.

2 EPILEPSY DETECTION AND EEG SIGNALS

2.1 Previous research

2.1.1 Applications of epilepsy detection

Epileptic seizures are caused by the sudden excessive electrical discharge of neurons of the brain. Hyper-excited and hyper-synchronized neural network leads to various symptoms, such as convulsions or lapse in attention and memory. The specific symptoms vary depending on the regions of the brain, involved in the seizure activity, the extent of the electrical discharge of neurons and its spread [1], [3].

The occurrence of seizures is highly unpredictable, which, combined with their outcomes, leads to the serious decrease in the quality of life of a person, his family and friends. The danger of injuries and the risk of SUDEP (Sudden Unexpected Death in Epilepsy) brings chronic anxiety and the need to rearrange daily life [1]–[4].

Systems that are able to detect or predict epileptic seizures can have various applications. In the clinical setting, detection of the seizure on its onset might enable rapid reaction, such as initiation of functional neuroimaging, or alert physicians, so that they could give anticonvulsants to patients [3].

Prescription of the antiepileptic medications is typically based on the patient diaries, which usually lack the accuracy. Automatic seizure detection might allow gaining more reliable statistics and summaries of seizure events. Accurate prescription of medications is important to avoid toxic effects and to achieve effectiveness of treatment [2], [3].

If implemented as a mobile closed-loop system, epilepsy detector or predictor might increase the comfort of daily life. It could give warnings of the upcoming seizures to the patient, so that he could reduce the danger from the environment. The alarms to the patient's physician and relatives could be sent allowing for fast help. In addition, immediate treatment could be given to the patient, for example triggering of neurostimulation such as VNS (Vagus Nerve Stimulation) or performance of neurofeedback practices [2], [3], [5].

2.1.2 Signals for epilepsy detection

Various types of signals have been studied in the context of epilepsy detection. One of the most valuable and reliable sources of information for epilepsy detection is EEG (or scalp EEG) and iEEG (or ECoG; intracranial EEG or Electrocorticography). These types of signals provide a mapping of neural activity of the brain. EEG, collecting electrical potentials from the surface of the scalp, allows higher spatial coverage, but lower spatial resolution, as it summarizes the activity of larger areas of the brain. In turn, iEEG, having electrodes directly exposed to the surface of the brain, gives higher spatial resolution as it is more accurate and summarizes more localized brain areas. Moreover, iEEG electrodes could be placed so that they collect signals from deeper regions of the brain, which is not possible in EEG. The need for surgical intervention during iEEG limits the spatial coverage, as well as the scope of usage [1]–[3], [7], [8].

Epileptic seizures may result in the deviations of the heartbeat, which enable the use of ECG (Electrocardiography) for the detection purposes. It is mostly useful for detecting seizures of newborns, because of the complications in usage of EEG signals. ECG has also been used for epilepsy detection in adults, but is more complicated due to the higher variations in signals during the day [2].

Accelerometers or motion sensors provide valuable information about the body movements. Specific movement patterns can be found for the purposes of detection motor seizures. Motion signals can be used for detecting only ongoing seizures. Accelerometers might be implemented as wrist or ankle bands, or be incorporated into the smartphones. Trials of epilepsy detection systems based on the motion data has already been conducted. The results show high false alarm rates, probably due to the confusion of some of the movements of daily life with seizure movement patterns [2].

Video analysis systems, with or without markers worn by patients, have also been adapted for seizure detection. Their drawback is the limitations in area, covered by the video camera. Mattress sensors, based on the audio or quasi-piezoelectric signals, aim to detect seizures during sleep. Other potential systems and signal types exist as well [2].

2.1.3 EEG and epilepsy

EEG and iEEG represent the electrical activity of neural networks of the brain. Thus, they have been utilized in various brain-related applications. They include characterization of sleep phenomena, studies of Creutzfeldt-Jakob disease, studies of nonlinear changes in encephalopathies and monitoring the depth of required anesthesia. Other applications also exist, such as emotion recognition, user authentication, neurofeedback practices, and detection of attempted movements [1], [4], [5], [9]–[11].

In the context of epilepsy, EEG of a patient contains valuable information about the specifics of neural activity of the brain during the seizure. Three states of epileptic EEG signals can be distinguished: ictal (during the seizure), pre-ictal (right before the seizure) and inter-ictal (between seizures). These states of EEG signals differ in various characteristics, which can serve as features for the seizure detector. Methods for EEG signal analysis can be divided into time domain methods, frequency-domain methods, time-frequency (wavelet) domain methods and nonlinear methods, including entropy-based methods. Nonlinear methods have proved to be specifically useful due to the high nonlinearity of the EEG signals [1], [2], [4], [12].

Closed-loop mobile systems for the detection of epileptic seizures, incorporating EEG signals, have also been studied. Data acquisition equipment varied from specifically designed devices to commercial EEG headbands, such as Emotiv Epoc [6]. The proposed devices for carrying out analysis of the incoming EEG data included computational units of the acquisition devices, mobile devices connected to the acquisition device and stationary data processing systems that receive signals by wireless means [2], [4], [13].

2.2 Potential to use commercial EEG headbands

Usage of commercial EEG headbands might be beneficial for the implementation of closed-loop mobile systems for the detection of epileptic seizures. They would eliminate the need for developing and producing new specialized equipment and allow implementing the system by conventional means. Suitability of the commercial headbands for the epilepsy detection problem requires studies, as the characteristics of the signals might differ from those of

clinical EEG devices due to the differences in technical parameters of the equipment and in the environment of usage.

To the best of author's knowledge, no databases exist for epileptic EEG signals, acquired with the commercial EEG headsets, such as Emotiv Epoc [6]. Such data is needed for the evaluation of the effectiveness of existing algorithms for epilepsy detection applied to the signals from commercial headbands and for tuning of those algorithms, as well as for the development of new algorithms. Collection of the mentioned data would require considerable time, organizational effort and funding.

This research aims to prove the potential to use commercial EEG headsets for epilepsy detection problem by emulating signals from those devices. The emulation is based on the existing database of clinical epileptic EEG signals. The parameters of the records are changed towards the parameters of a commercial EEG headset. The baseline device, considered in this work, is Emotiv Epoc [6].

The performance of a chosen epilepsy detection algorithm is estimated before and after emulation of different signal parameters. The characteristics, emulated in this research, are:

- referencing scheme;
- subset of electrodes used;
- sampling rate;
- sample resolution;
- additional noise level.

The emulation is performed in a step-wise manner (i.e. one characteristic is changed at a time). Performance is evaluated after each emulation step. Such evaluation scheme allows comparing of the impact of each emulation step on the system performance. All the evaluations utilize the same detection algorithm with the fixed set of internal parameters.

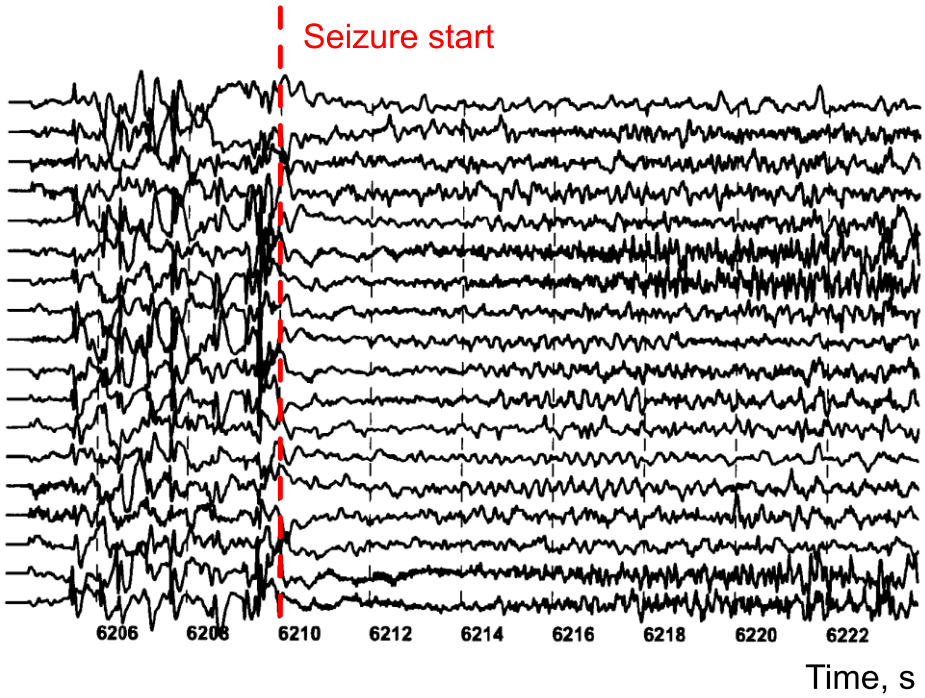
In general, performance evaluation for each emulation is as follows. The original data is loaded and transformed in the ways that would emulate the chosen parameters. The transformed data is fed to the epilepsy detection algorithm, where it is used for training and performance testing in the cross-validation manner. The result of cross-validation serves as an estimate for the detection performance of the algorithm, applied to the emulated data.

3 ALGORITHM FOR DETECTION OF EPILEPTIC SEIZURES

3.1 Chosen patient-specific algorithm

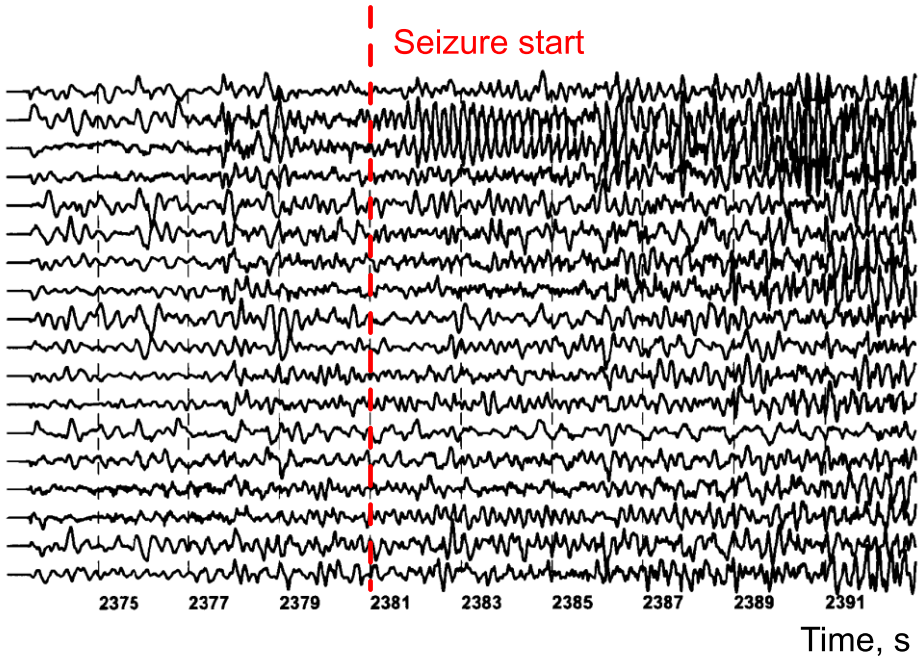
This section will discuss the epilepsy detection algorithm used in this work for estimating detection performance on differently emulated data. The algorithm, proposed by Shoeb [3], will be explained in detail and the deviations from it, as well as additional decision made during the implementations, will be stated.

The selected algorithm is patient-specific. In his work [3], Shoeb mentions, that the seizure activity seen on the EEG signals varies a lot between different patients, but may stay similar for one patient within months. Example of visible intrapatient similarities and interpatient dissimilarities is demonstrated in Figure 1. Choice of the patient-specific approach to the detection, in which the detector is trained on the data of only one patient, is reported to improve its performance [3].



(a)

Figure 1. Intrapatient and interpatient variability of seizure EEG activity.



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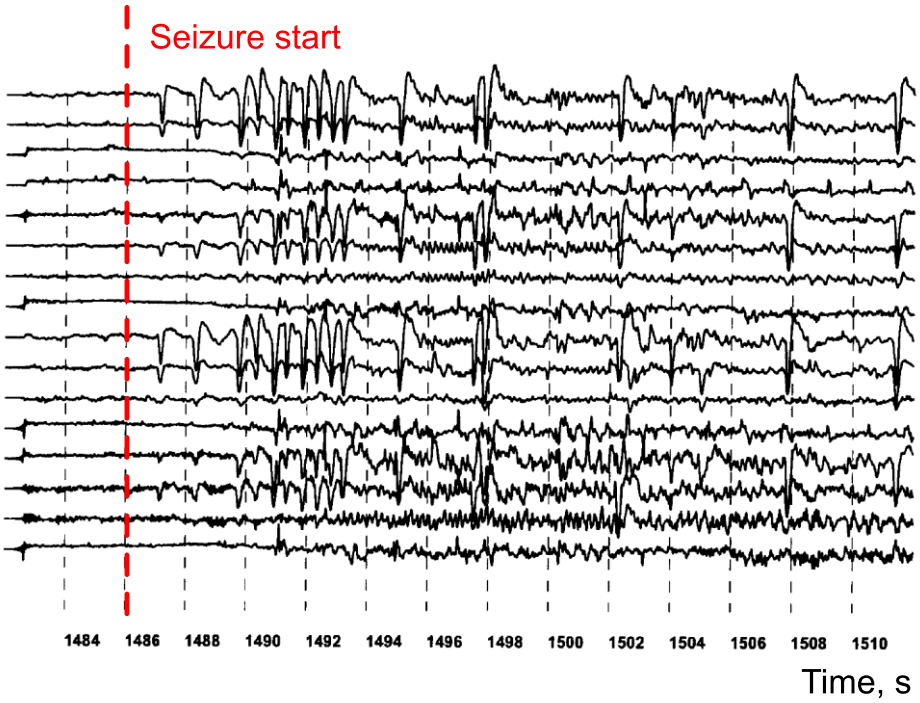
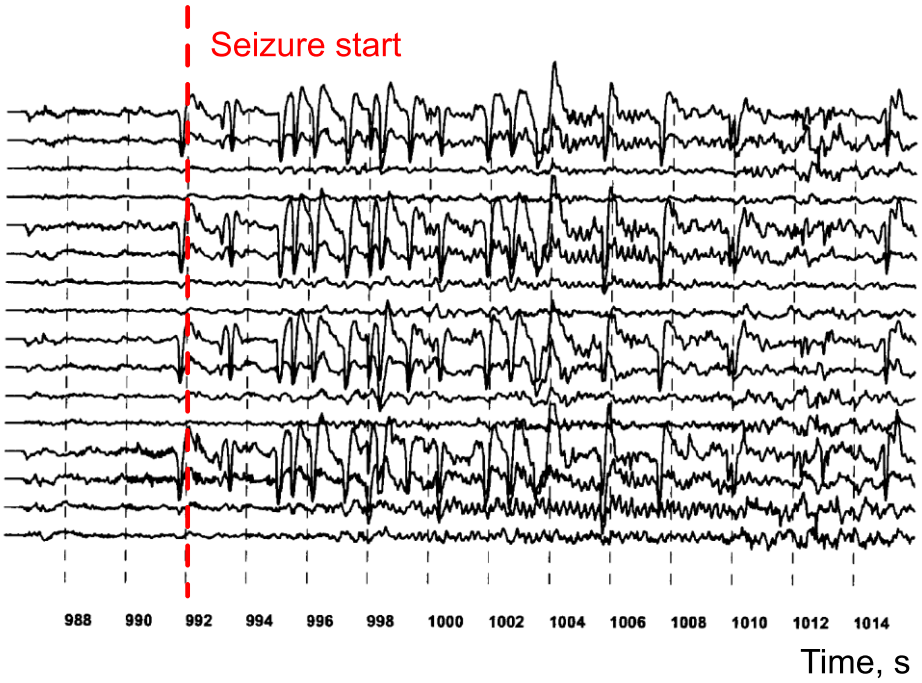


(c)

Figure 1 (continued). Intrapatient and interpatient variability of seizure EEG activity.



(d)

Figure 1 (continued). Intrapatient and interpatient variability of seizure EEG activity. (a) Epileptic EEG of patient A; seizure starts at 6210 seconds. (b) Epileptic EEG of patient B; seizure starts at 2381 second. (c) Epileptic EEG of patient C; seizure starts at 1486 seconds. (d) Epileptic EEG of patient C; seizure starts at 992 seconds; recorded approximately 10 months after (c). The visual difference between seizures of patients A, B and C is clearly seen, as well as the similarity of the two seizure apperances of patient C. Adapted from the work of Shoeb [3].

3.2 Detection problem

EEG signals constitute time series, for which the detection is usually performed with the use of the sliding window approach. Since the only varying parameter in the time series is time, the signals are 1D in the sense that the detection window is sliding only in one dimension. In each position of the sliding window the detection is performed, based on the data, covered by the window.

Let us consider an example of the sliding-window detection on the signal with the scalar-valued function. In each position of the window, the number of samples, covered by it, is defined by the size (duration) of the fragment under the window T and the sampling rate of

the data s as $n = T \cdot s$ (the notion of the sampling rate will be discussed in Section 4.5). These n samples are the input of the detector.

An EEG signal is commonly multidimensional. It consists of c channels, together forming a multidimensional time series. The samples of several channels at each time point can be combined into a vector, thus making a function of a signal vector-valued. In that case, sliding detection window covers fragments of vector-data, but remains 1D, changing its position only in time. The number of data samples under the window becomes $n = c \cdot T \cdot s$, where c is the number of channels, T is the duration of data fragment, covered by the window, and s is the sampling rate of data.

Sliding of the detection window is performed with some time step Δt. Batches of the signals under the window at each position are the input for the feature extractor. It summarizes the most relevant attributes of each signal fragment. These attributes, combined into feature-vectors, are then passed the classifier, which performs binary classification. The batches containing some sought-for property are distinguished from the rest of the fragments. In the case of epilepsy detection, this property is the seizure activity. The features extracted from the signal are supposed to ease the classification, so their relevance is determined by the task.

The classifier should be trained with the examples* of seizure and non-seizure feature-vectors. These examples are extracted from the labeled training data. If the data contains the labels for seizures only in the form of the time of their start and end, special sorting rules should be applied to determine, which fragments should be considered as seizure fragments, and which are non-seizure ones. The rule used in this work is based on the explanations of Shoeb [3]. The fragment is considered belonging to the seizure class, if it at least partially overlaps with the period of seizure activity, and is considered to belong to the non-seizure class otherwise.

The Shoeb's detection algorithm aims to detect the seizures in their onset. For that reason, only the examples, located near the start of the seizure, are passed to the classifier for the

* In the context of classification, examples are also called samples. This name is intentionally avoided here, not to be confused with the data samples.

training. The duration of the seizure onset O is fixed for all seizures. All the seizure-examples, that are located further than the onset duration O from the seizure start, are excluded from the training set. If the seizure duration is shorter than the chosen onset duration parameter O, all the fragments of that seizure get to the training set.

The parameter of the sliding step, recommended in Shoeb's work [3], is $\Delta t = 1$ sec, and the parameter of seizure onset is recommended to be $O = 20$ sec. The size of the sliding window will be discussed in the next section, as it is defined by the features, extracted from the signal.

3.3 Feature extraction

3.3.1 Spectral features

The basic features used in the Shoeb's work [3] are derived from the spectral distribution of the signal. As Shoeb states, the most relevant information of EEG signal is contained in the frequency band 0-24 Hz. The example comparison of the spectra of one EEG channel of a patient in different states is shown in Figure 2. It is clearly seen, that the spectra have significantly different energetic distribution in the chosen spectral band.

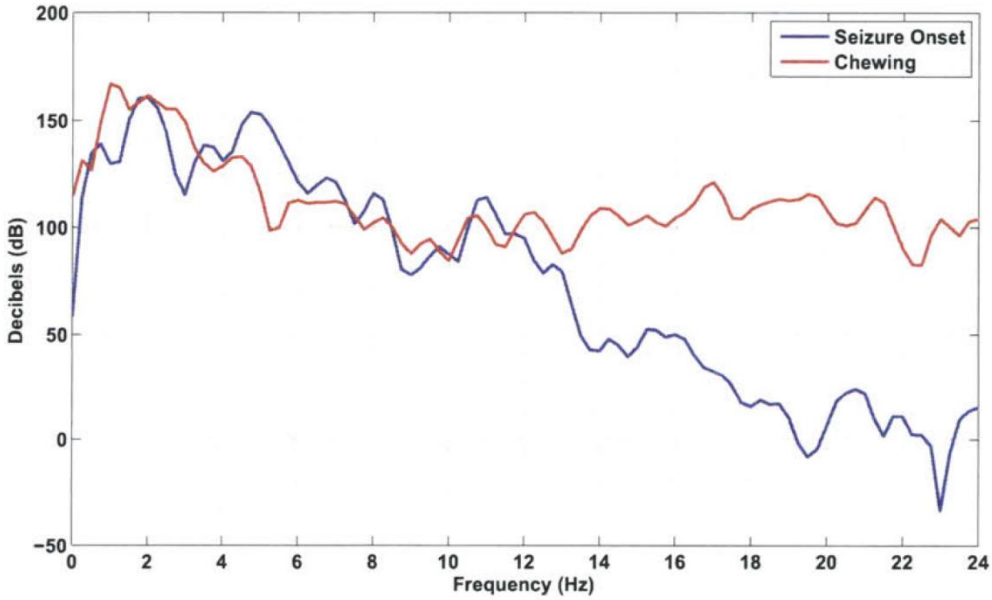


Figure 2. Superposition of the frequency spectra of chewing and the rhythmic activity following the onset of the seizure. The seizure spectrum contains less high-frequency content relative to the chewing spectrum [3].

In order to construct a feature-vector, based on the spectral information, Shoeb proposes to divide that spectral band into m sub-bands using a filter bank. The number of the bands is recommended to be $m = 8$. The spectral energies from each sub-band are then calculated and combined into the feature-vector. The spectra are calculated from the fragments of the signal of the duration T_{spec}. The recommended value for the fragment duration is $T_{\text{spec}} = 2$ sec. The illustration of the extraction of spectral energies of sub-bands is given in Figure 3.

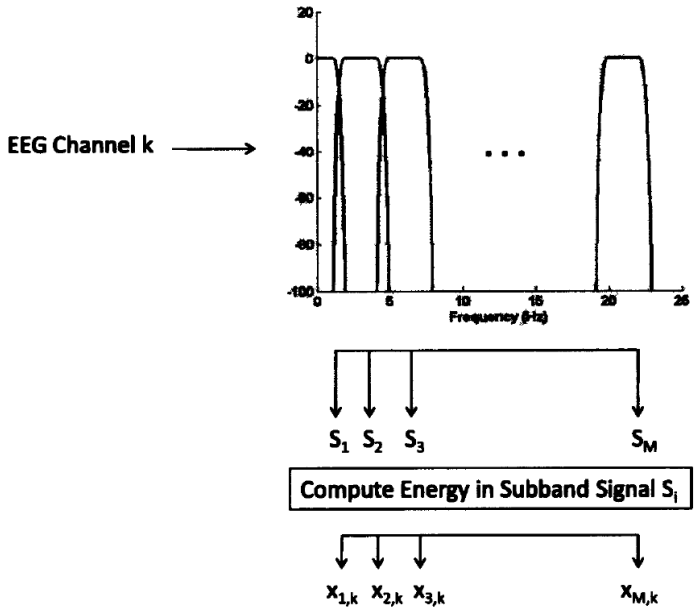


Figure 3. Extraction of spectral features. M-band filterbank measures the energy within the spectral components of a fragment taken from a k-th EEG channel [3].

As the signal is digitized, the discrete representation of the spectrum is calculated in this work using the MATLAB implementation of Fast Fourier Transform (FFT) [14]. The extraction of the spectral energy of each sub-band becomes then just the summation of a subset of the discrete values of energetic spectrum, belonging to that sub-band. Each value in the energetic spectrum is calculated as a squared magnitude of the original complex-valued Fourier spectrum.

Finally, in the implementation used in this work, not the energy values of sub-bands are encoded in the feature-vector, but their decimal logarithms. This is similar to the conversion of values to decibels (dB), but omitting multiplier terms. This step showed to increase the

performance of the system, although no thorough experimentation was conducted in this work.

3.3.2 Spatial features

Spectral features, discussed previously, are extracted from one channel of the EEG signal fragment. Different channels of the signal represent spatial differences in EEG, as they are formed using electrodes in different spatial locations. As Shoeb stated [3], this spatial information might be important, because seizure activity tends to spread wider than other normal electrical activities.

To incorporate that spatial information in the feature vectors, Shoeb proposes to concatenate the spectral features, obtained from different EEG channels in the same fragment, into one feature-vector. If the order of the channels stays the same in all the data records of a patient, concatenation of the spectral features will also preserve the information about the relationships between channels (as opposed to, for example, averaging of the features).

3.3.3 Temporal features

Shoeb states in his work [3], that the evolution of the spectral features might constitute a valuable source of information for the seizure onset detection. He explains that seizures are often emerging from the background EEG in the specific patterns of events. Thus, he proposes to capture this time-evolution information by concatenating the spatiospectral feature-vectors from W subsequent non-overlapping fragments of the signal. The number of concatenated spatiospectral features is recommended to be $W = 3$. The length of the signal fragment, covered by the final feature-vectors, (i.e. the duration of the sliding detector window) becomes $T = T_{\text{spec}} \cdot W = 6$ sec.

The process of obtaining the final features, that combine spectral, spatial and temporal information, is shown in Figure 4. It should be noted, that most of the spatiospectral features are included in several different final features. For the sake of computational efficiency, those features should be calculated only once. In the offline-case of the classifier training, the calculations and combinations of primary features can be computed record-wise, as is implemented in this work. In the case of online detection, when the new data is received

gradually, the features, that are already computed and need to be reused in the future, can be stored in the buffers.

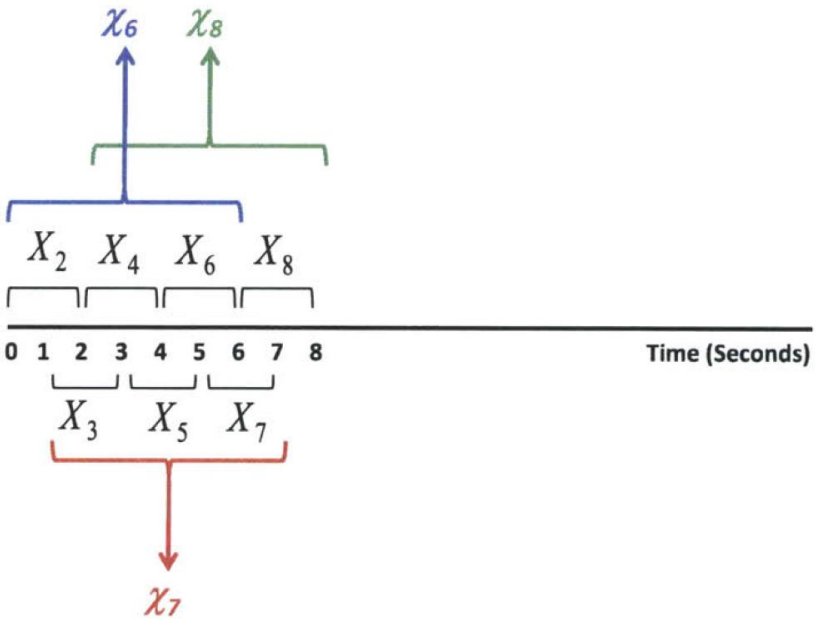


Figure 4. Construction of the final features χ from the spatiospectral features X. Indices represent the last second, covered by the feature [3].

3.4 Classification

Following Shoeb's work [3], in this research SVM (Support Vector Machine) was used as the classifier. It determines the hyperplane in the feature space, which separates examples of two classes and achieves the largest margin between them. In the non-separable problem, as is the problem of seizure detection, SVM finds the boundary that separates many of the training samples, but not all of them.

The non-linear version of SVM searches for the linear boundary in the higher-dimensional feature space, introduced by the kernel. This results in the selection of the non-linear decision boundary in the original space. The illustrative example of the results of class separation with SVM is shown in Figure 5.

In this work, the MATLAB's implementation of SVM [15] is utilized. Non-linear kernels were not applied here, which is the default option of the MATLAB's SVM. In contrast, Shoeb used the radial kernels for the SVM classification [3].

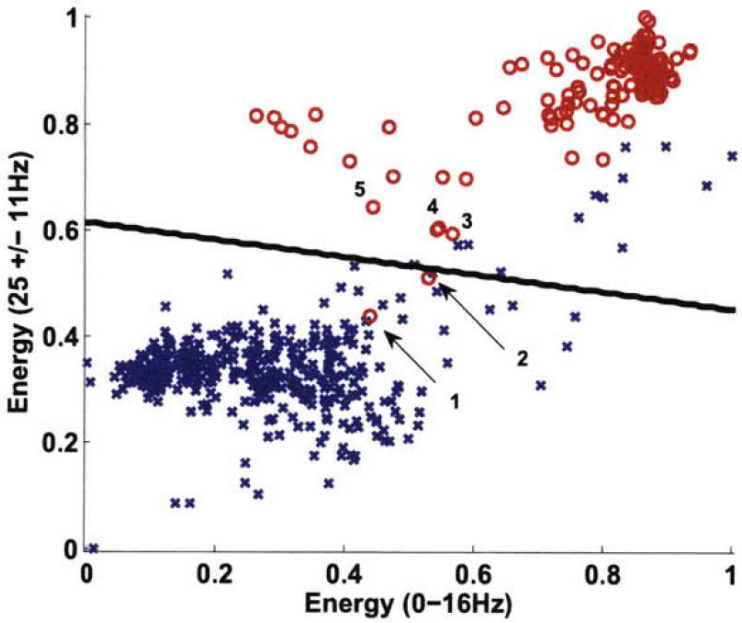


Figure 5. Linear decision boundary separating seizure (red) and non-seizure (blue) feature vectors extracted from a single iEEG channel. The first dimension of this feature space is defined by the energy in the spectral band 0-16 Hz and the second dimension corresponds to the energy in the 25 ± 11 Hz band. The seizure vectors extracted from the first 7 seconds of the seizure are numbered 1-5. The decision boundary was determined using the SVM learning algorithm [3].

3.5 Performance evaluation

This work utilizes the same dataset of epileptic EEG signals ([16], [17]) as is used in Shoeb's work [3] (this data will be discussed later). The data is divided into records, which enables to use leave-one-record-out cross-validation scheme, proposed by Shoeb. According to that scheme, each of the records is tested by the detector, trained on the rest of the patient's records. This allows testing all the data while not having any record both in the training and in the testing set at the same time.

The variables, used to estimate the detection performance, are sensitivity and specificity. Following Shoeb [3] sensitivity is defined as the percentage of the seizures, that are detected. Specificity, in turn, is defined by the frequency of false alarms (i.e. the number of false alarms per hour of data). Shoeb also uses the parameter of the detection delay (the delay,

with which the system is able to detect the seizure). This parameter is not used in this research.

In this work, the calculation of sensitivity and specificity is performed as follows. Each seizure is considered detected, if any of the features, extracted from the fragment of signal with seizure activity, is classified as belonging to the seizure class. The seizure is considered missed otherwise. In contrary, any feature detected as the seizure-one, lying outside the time range of all the labeled seizures, is considered as one false alarm (FA).

For each record, the number of seizures detected and originally contained in it is saved, as well as the number of false alarms and the duration of the record. To obtain the overall statistics, these values are accumulated along the records (and subsequently along the patients). Finally, sensitivity is calculated by dividing the overall number of detected seizures by the number of originally labeled seizures. Similarly, the false alarm rate (specificity) is calculated by dividing the overall number of false alarms by the overall duration of all the tested data records.

4 EMULATION OF EEG SIGNALS FROM A COMMERCIAL DEVICE

4.1 Motivation

This research aims to estimate the changes in the performance of detection of epileptic seizures, when the EEG acquisition equipment is changed from the clinical type to the commercial. A number of technical characteristics differ among those EEG devices. Since no existing database of epileptic EEG signals from commercial headbands is known to the author, this research proposes an emulation of such signals, based on the existing clinical dataset.

The estimate of the detection performance change should prove the feasibility to use commercial EEG headset in context of seizure detection. The main features of EEG, which are related to seizures, are expected to be preserved during the device switch and its emulation. Further research, related to the collection of the real data, might be triggered after proving the concept.

In this work, the change of the device characteristics will be emulated by transforming CHB-MIT clinical epileptic EEG data [16]. Parameters of Emotiv Epoc device [6] are taken as the main target during the emulations. The emulation is performed in a step-wise manner: each next change of the data parameters (emulation step) is performed on top of all the previous steps. This section aims to describe the emulations, made within this research, and some details of their implementations.

4.2 Description of original data

The CHB-MIT dataset [16], used in this work, was collected in Children's Hospital Boston. It contains 664 recordings with 198 seizures from 24 patients. The data was recorded during the monitoring of the subjects for the assessment of their candidacy for surgical intervention. The signals were collected continuously and contain EEG of subjects in different states during a day.

Electrode positioning was performed according to the 10-20 system [18], which specifies locations and labeling of the electrodes. The set of electrodes, used in the CHB-MIT data is depicted in Figure 6.

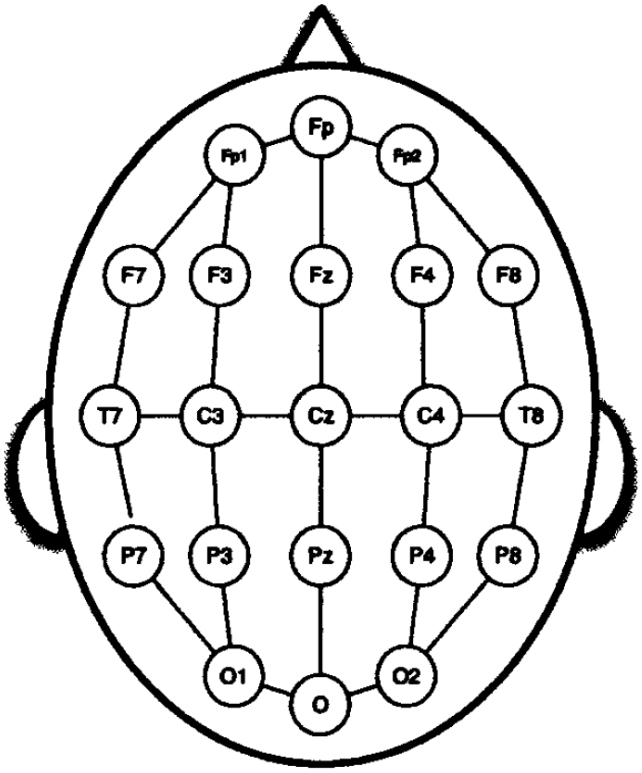


Figure 6. Set of EEG electrodes used in CHB-MIT dataset [3].

Some of the recordings have variations in the set of the used channels. In some cases records lack a subset of EEG channels, in some additional channels are included, such as ECG or VNS channels. Some records also include dummy signal channels meant to improve readability of the data. The order of the channels is also a subject to variations.

In this work, only those records were used, from which a standard subset of 23 channels could be extracted (in the fixed order). This resulted in the choice of 653 records, containing 180 seizures. The records have a total length of 951 hour.

Reading of the data was performed with the utilization of the function `readedf` from the EEGLab toolbox for MATLAB [19]. The function was edited by the author of this work for the sake of memory and speed optimizations.

4.3 Referencing schemes

EEG signal channel is typically recorded as the difference between the potentials on two electrodes: an active electrode and a reference electrode [20]. Different selection of the active and reference electrodes results in different referencing schemes. One scheme, which was used during the recording of CHB-MIT dataset, each active electrode is referenced to one of its neighbors. Another scheme, used in the commercial devices, such as Emotiv Epoc, refers all active electrodes to one or to reference electrodes.

These differences might have an impact on the distribution of spatial information along the recorded channels. Thus, the first emulation step in this work is the changing of electrode referencing. This is achieved by adding and subtracting original data channels. The formulae for the calculations are given in the Table 1.

Table 1. Formulae for changing the referencing scheme of the data. Input channels are from CHB-MIT dataset. Output channels are emulating referencing scheme of Emotiv Epoc.

Input channels	**Output channels**
X1 = FP1 – F7	Y1 = FP1 – P3 = X1 + Y2
X2 = F7 – T7	Y2 = F7 – P3 = X2 + Y3
X3 = T7 – P7	Y3 = T7 – P3 = X3 + Y4
X4 = P7 – O1	Y4 = P7 – P3 = X4 – X8
X5 = FP1 – F3	Y5 = O1 – P3 = –X8
X6 = F3 – C3	Y6 = F3 – P3 = X6 + X7
X7 = C3 – P3	Y7 = C3 – P3 = X7
X8 = P3 – O1	Y8 = FP2 – P4 = X9 + Y9
X8 = FP2 – F4	Y9 = F4 – P4 = X10 + X11
X10 = F4 – C4	Y10 = C4 – P4 = X11
X11 = C4 – P4	Y11 = O2 – P4 = –X12
X12 = P4 – O2	Y12 = F8 – P4 = X14 + Y13
X13 = FP2 – F8	Y13 = T8 – P4 = X15 + Y14
X14 = F8 – T8	Y14 = P8 – P4 = X16 – X12
X15 = T8 – P8	Y15 = Fz – Cz = X17
X16 = P8 – O2	Y16 = Cz – Pz = X18
X17 = Fz – Cz	Y17 = FT9 – P3 = Y3 – X20
X18 = Cz – Pz	Y18 = FT10 – P4 = X22 + Y13
X19 = P7 – T7	
X20 = T7 – FT9	
X21 = FT9 – FT10	
X22 = FT10 – T8	
X23 = T8 – P8	

The referencing was set to Electrodes P3 for the left hemisphere and to Electrode P4 for the right hemisphere. This resembles the referencing scheme of the Emotiv Epoc device [6], but the author is unsure, that the referencing is performed exactly the same way on that device.

It can be seen that the number of output channels after that operation is less than the number of the input channels. This happened because of the redundancy in the data. Some of the channels were repeated in the recordings (with the same or different sign). Some of the electrodes are included in the original channels more times than others, which also introduces redundancies.

The physical effects of altering the referencing scheme are not guaranteed to be the same as the result of the mentioned algebraic expressions. However, this emulation step allows separating signals from particular electrodes and perform the selection of their subsets.

4.4 Selection of electrodes

Data from the CHB-MIT dataset after the change in referencing includes 18 channels, formed with 21 electrode. Emotiv Epoc has 14 channels, formed by 16 electrodes. Therefore, the next emulation step is to select a subset of channels and electrodes used.

Unfortunately, not all the electrodes from Emotiv Epoc set are present in the CHB-MIT data. For that reason, the basic subset of channels used in this emulation step contains only 10 channels formed by 12 electrodes. These channels have the exact match between the sets. The sets of Emotiv Epoc and CHB-MIT electrodes are shown superimposed on the Figure 7.

Selection of other subsets of electrodes was also studied in this work. These subsets include the following:

- Extended set of 14 electrodes, based on the Emotiv Epoc electrode locations (missing electrodes are substituted with the neighboring electrodes, contained in CHB-MIT dataset; channels Y1-Y14 from Table 1).
- Additional set of 10 channels, different from the Emotiv Epoc (channels Y1, Y4, Y5, Y7, Y8, Y10-Y12, Y17 and Y18 from Table 1).

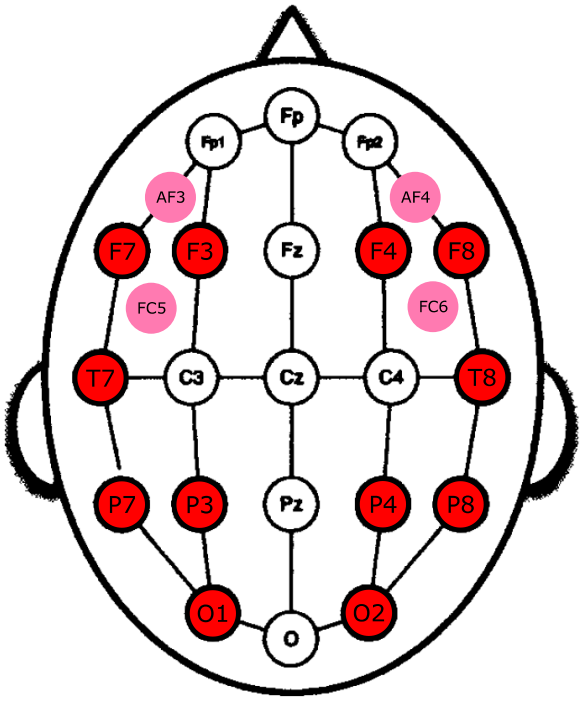


Figure 7. Comparison of electrodes of CHB-MIT dataset and Emotiv Epoc device. The circles with black border represent electrodes present in CHB-MIT data. The red circles represent Emotiv Epoc electrodes, present in CHB-MIT data. The pink circles represent Emotiv Epoc electrodes, not present in CHB-MIT data. Adapted from the work of Shoeb [3].

- Set of 5 channels, somewhat representing electrode locations in Emotiv Insight [21] (see Figure 8; 2 of 5 active electrodes from Emotiv Insight are not used in the CHB-MIT dataset and are replaced by their neighbors; the reference electrode is also not present, thus referencing to electrodes P3 and P4 is preserved; channels Y1, Y3, Y8, Y13 and Y16 from Table 1).
- Additional set of 5 channels, different from the Emotiv Insight setup (channels Y5, Y11, Y15, Y17 and Y18 from Table 1).

4.5 Sampling rate

Analogous signals are typically discretized, if they are meant to be digitally analyzed. Discretization is the process of representing a continuous signal as an array of discrete values, samples. The rate of extraction of these samples defines the maximal Fourier-frequency of

the signal that can be represented without loss. Thus, the sampling rate defines the level of details, with which a signal can be digitally encoded.

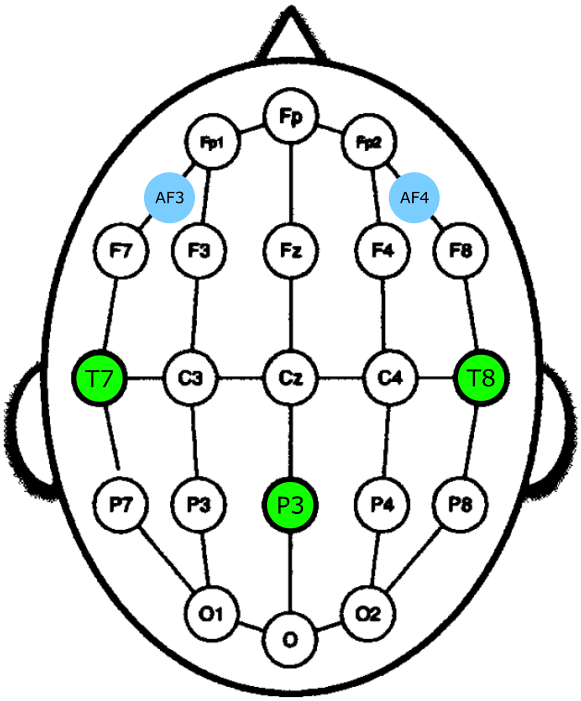


Figure 8. Comparison of electrodes of CHB-MIT dataset and Emotiv Insight device. The circles with black border represent electrodes present in CHB-MIT data. The green circles represent Emotiv Insight electrodes, present in CHB-MIT data. The blue circles represent Emotiv Insight electrodes, not present in CHB-MIT data. Adapted from the work of Shoeb [3].

The signals from CHB-MIT dataset have the sampling rate of 256 Hz, while the sampling rate of commercial devices may be lower. In the Emotiv Epoc device, two options of sampling rate are available: 256 Hz and 128 Hz. For the Emotiv Insight, only the value of 128 Hz is available.

In this research, the change in sampling rate is emulated by resampling of the original CHB-MIT signals to the targeting sampling rate. The basic parameter, chosen to emulate Emotiv Epoc, is 128 Hz. Other values of sampling rate, studied in this work, vary from 32 Hz to 192 Hz (they will be discussed in the Section 5.3.2). Resampling is performed after changing the referencing scheme and selecting the subset of 10 Emotiv electrodes.

The resampling routine utilized the MATLAB function `resample` [22]. It applies antialiasing FIR filter (Finite Impulse Response) before performing the resampling. By default, the interpolation method is linear.

4.6 Sample resolution

In order to digitize the signal fully, besides discretizing it in time one needs to quantize its continuous amplitude. Quantization maps the values of the signal at the sampling points to the nearest discrete value, that can be represented digitally. As these values are typically encoded in bits, the sample resolution (i.e. the accuracy of quantization) is therefore measured in bits per sample (bps). The larger number of bits used to encode each sample allows distinguishing more levels of signal amplitude.

CHB-MIT signals are encoded with 16-bit precision, whereas Emotiv Epoc has the options for sample resolution of 16 bits or 14 bits. For the emulation, the lower value of 14 bits is used as a basic target sample resolution. Other values of sample resolution are also studied in this work. Their values vary from 6 bits to 12 bits (they will be discussed in more detail in Section 5.3.3). Changing of the sample resolution is performed after the change in referencing, choice of the subset of 10 electrodes from Emotiv Epoc, and lowering the sampling rate to 128 Hz.

Change of the sample resolution is performed by discarding of the least significant bits. This can be performed with the operation of shifting to the right by the number of bits, equal to the difference d between the original k and targeting l resolution ($d = k - l$). Such an operation is equivalent to the integer division of the value by 2 the number of times, equal to the number of bits being discarded (d). These divisions could also be performed in one step by dividing by the value 2^d. The rounding in that case is always downwards (floor operation).

In this work, an ordinary bit shifting is substituted with the division by 2^d, but with rounding to the nearest integer. That is assumed to emulate the original process of analog signal quantization better, since the values there are typically quantized to the nearest possible value, but not downwards.

The resulting values are multiplied back by the same value of 2^d, which is similarly equivalent to the shifting to the left by d bits. This operation allows preserving the original scale of values after the loss of information during rounding.

Retaining of the scale is important, as the scale of the signal affects the scale of feature-values that are extracted from it. The SVM classifier, used in this work, was not set to rescale the input features. Thus, the result of its work might be different, if the feature values in the training set are scaled differently, even if they preserve all the relationships between each other. To eliminate the impact of the changes in the scale of signals on the performance and to retain only the effects of lowering of the sample resolution (i.e. the accuracy of representation of values), the scale of signals is preserved.

4.7 Noise

The last emulation step is the introduction of additional noise to the signals. The acquisition systems of commercial devices are presumed to be noisier than the clinical systems, due to the usage of different electrodes with different quality of contacts and other technical differences.

The study and comparison of system noise was not possible within this work. Thus, the model of the noise distribution, as well as its parameters, was chosen arbitrarily. However, the study of the sensitivity of the detector to the introduced of additional noise should be still valuable.

The model for the additional noise was chosen to be the white Gaussian noise. It was generated in this work with the use of MATLAB function `wgn` [23]. This function takes a power of noise p in decibels as an input, but it has no physical meaning for this work. Therefore, only the standard deviation σ (SD) of the noise signal received is of importance. It is related with the power of the noise as $p = 20 \log_{10} \sigma$.

In the emulation of this work, the noise is added to the signal before all the other emulation steps. This is done to emulate addition of the noise to the analogous signal before its sampling and quantization. For the quantization step, it is particularly important, since addition

of the noise before the changing of the sample resolution, as it is implemented in this work, would introduce the values of the signal lying between the allowed discrete levels.

However, addition of the noise before the reference changing might introduce uneven distribution of the noise between the output channels. Some of the output channels are obtained by combination of larger number of the original channels. That will increase the noise level for them, since the noise level from all the combined channels is accumulated. This fact is not handled in this work.

The basic parameter of the noise power, chosen for emulation of Emotiv Epoc signals in this work, is $p = 20$ dB, which corresponds to the SD $\sigma = 10$. Other values of noise power, considered in this work, vary from $p = 5$ dB to $p = 60$ dB, which corresponds to varying of SD from $\sigma = 1.78$ to $\sigma = 1000$ (these values will be discussed in more details in the Section 5.3.4). For the comparison, the range of possible values of the signal, based on the 16-bit precision, is from -32767 to 32768. In practice, the real range of signal values seems to be somewhat narrower.

5 EXPERIMENTS AND RESULTS

5.1 Motivation

The experimentation, conducted within this research, has two main goals. The first goal is the estimation of the change in performance of detection of epileptic seizures, when the EEG acquisition equipment is switched from the clinical to the commercial. The second goal is the estimation of the ranges of acceptable variations in the characteristics of equipment and data.

Each experimental result is gained with the same procedure. First, the set of emulation parameters is selected, depending on the experiment, after which the data transformation is performed. Transformed data is fed to the detection algorithm for training and testing. The detector has the constant settings throughout all the experiments. Finally, evaluation of the detection performance is conducted with the standard routine.

Each evaluation of the detection performance is conducted only once in this research. The process of data transformation and retraining of the classifier is computationally intense. Due to the technical limitations, multiple detector evaluations on the same emulated data were not possible. Thus, the effects of the possible variations in training results are not taken into consideration.

Another consequence of one-time evaluation of the detector on each emulated dataset is the inability to construct ROC curves (Receiver Operating Characteristics). Each performance result is presented as one point on the ROC-plot. That limits the conclusions, which could be made from the results in some cases.

Two types of experiments will be discussed in this section. The first one compares the performance results after different emulation steps. Combination of all the steps emulates the usage of Emotiv Epoc device. The second one estimates the sensitivity of the detector to changes of the parameters of each emulation step. The ranges of parameters without significant performance change could serve as an estimate of the acceptable values.

5.2 Sensitivity of performance to emulation steps

The first experiment focuses on the comparison of impacts of different data characteristics on the detection performance. The emulation of the characteristics of equipment is step-wise in this work: one parameter is changed at a time. Each next data transformation is performed on top of the previous steps. The standard parameters of steps are chosen such that the characteristics reach those of the Emotiv Epoc device.

The emulation parameters, selected on each step within this experiment, are listed below.

- No parameters changed. The original data is preserved.
- Only the referencing scheme is changed (see Section 4.3).
- The subset of 10 Emotiv Epoc electrodes is selected after the referencing change (see Section 4.4).
- The sampling rate is lowered to 128 Hz on top of previous steps (an option of Emotiv Epoc; see Section 4.5).
- The sample resolution is reduced to 14 bps on top of previous steps (an option of Emotiv Epoc; see Section 4.6).
- The white Gaussian noise with power parameter of 20 dB is added to data, followed by performance of previous steps (arbitrary noise selection; see Section 4.7).

The results of detection performance evaluation for the listed data emulations are demonstrated in Figure 9. All the results are enclosed by the range of sensitivity from 90% to 95% and specificity from 3.0 FA/hour to approximately 4.3 FA/hour. All of the further results will be presented in a range of sensitivity 80%-100% and specificity 2.0-6.0 FA/hour, as most of the points are included in that range. Having the same scale of graphs eases their comparison. Additional graphs with other scales will be presented as needed.

First, the difference between the performance result on the original data and the results, reported by Shoeb [3], should be noted. The performance of the selected detection algorithm on the same data was reported to have the overall sensitivity of 96%. The false alarm rate

varies between 0 and 5 FA/24 hours (0.00-0.21 FA/hour) for 18 out of 23 patients* and reached 20 FA/24 hours (0.83 FA/hour) for one of the patients. The overall statistics for the specificity is not mentioned. The difference in the false alarm rate could be explained by the mentioned differences in the SVM classifier settings (linear vs. radial kernels; see Section 3.4). In addition, the differences in the evaluation of false alarm rates could occur, since in the original work, the meaning of one false alarm was not specified.

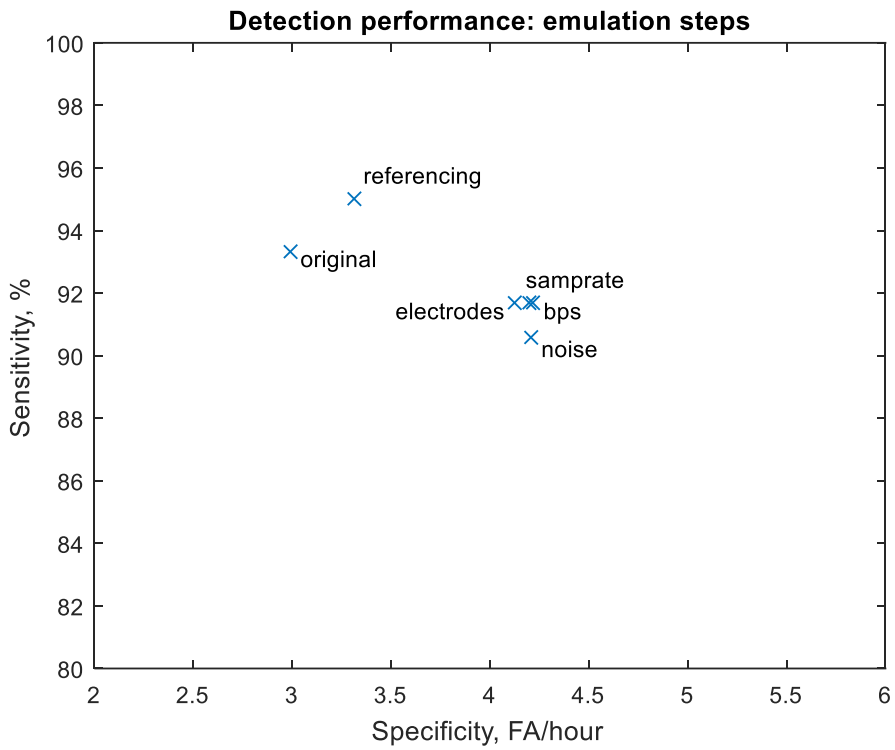


Figure 9. Evaluation of the detection performance after different emulation steps. Data emulation markers: `original` – original data; `referencing` – data with changed referencing scheme; `electrodes` – data after selection of 10 Emotiv Epoc electrodes; `samprate` – data with sampling rate, lowered to 128 Hz; `bps` – data with sample resolution, reduced to 14 bps; `noise` – data with additional white Gaussian noise with power parameter of 20 dB.

The performance on the original data and on the data with changed referencing scheme seems to differ insignificantly. However, the absence of ROC-curves makes the reasonable

* In the original work [3], the dataset from 23 patients was used. The data from 24th patient was recorded later.

comparison of the performance values, which have a tradeoff between sensitivity and specificity, impossible. Here, the difference will be assumed small enough to consider the two results to lie on the same curve.

In contrary, the performance on all the other steps is lower in both sensitivity and specificity values. The electrode selection step shows almost the same detection capabilities, than the change in sampling rate and sample resolution. The differences can be considered as caused by the training variations. Addition of the noise seems to lower the sensitivity somewhat further. Nevertheless, that difference seems to be significantly less, than from the performance on the original and differently referenced data. Thus, it might be neglected.

Figure 10 presents the comparison of the experimental performance results with the performance of random guessing. Random classification was implemented as the generation of random answers and their evaluation with the standard performance evaluation routine. A hundred values of seizure feature probability, equally distributed from zero to one, were utilized to enable ROC-curve construction. For each probability, 1000 trials were conducted, in order to estimate the average performance of random classifier. The curve should give an estimate of the shape of ROC-curves in the chosen coordinates. In addition, it should give some reference to the general detection quality.

For the data on each emulation step, the chosen detector significantly outperforms the random classifier. In the range of 90-95% of sensitivity, the random classifier has 200-300 FA/hour of specificity, which is about two orders of magnitude higher, than the false alarm rate of the detector, used in this work. Moreover, for all the results, falling into the range of 80-100% sensitivity and 2-6 FA/hour specificity, the performance is vastly higher, than that of the random guessing.

5.3 Sensitivity of performance to emulation parameters

5.3.1 Electrode subsets

The second type of experiment is devoted to studying of the effects of changing parameters of each emulation step. Four such experiments have been conducted. In each, one emulation parameter is chosen to be varied, while others are fixed. The parameters to vary are the subsets of electrodes to select, the sampling rate of data, the sample resolution and the level

of white Gaussian noise to be introduced. All the parameters of emulation steps, that come prior to the currently varied one, are chosen according to the Emotiv Epoc specifications, the same way as in the first experiment type (see Section 5.2).

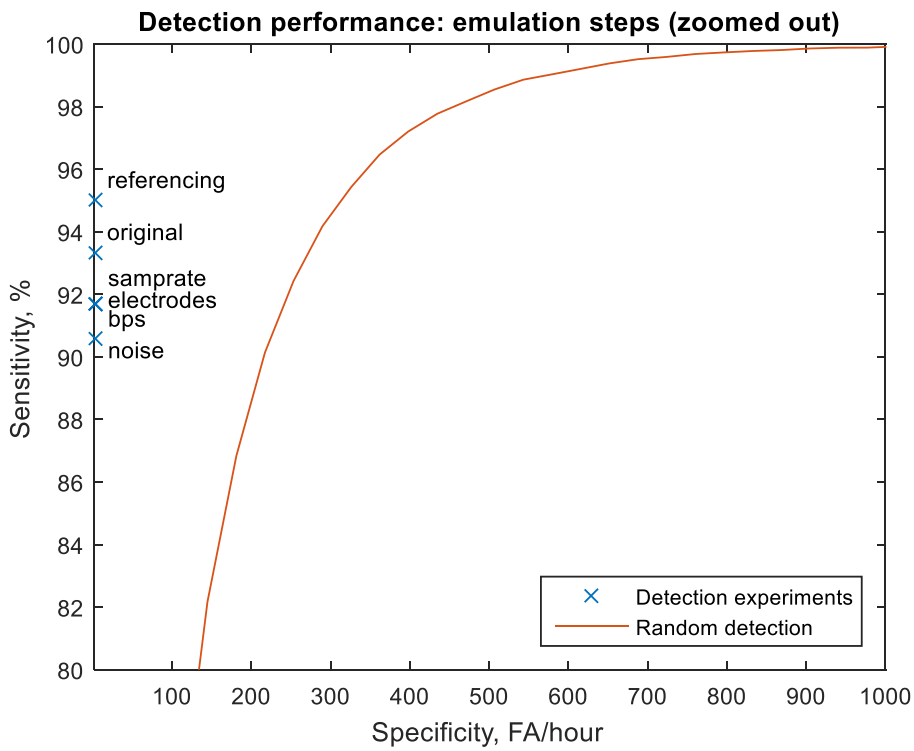


Figure 10. Comparison of the detection performance after different emulation steps with random detection results. The blue crosses represent experimental results. The red line represents the ROC-curve of random classifier. Data emulation markers: `original` – original data; `referencing` – data with changed referencing scheme; `electrodes` – data after selection of 10 Emotiv Epoc electrodes; `samprate` – data with sampling rate, lowered to 128 Hz; `bps` – data with sample resolution, reduced to 14 bps; `noise` – data with additional white Gaussian noise with power parameter of 20 dB.

Different variations of possible referencing schemes were not studied in this work. Thus, the first emulation parameter to vary was the selection electrode subsets. Each emulation here is performed after the change of the referencing scheme. Different tested combinations of electrodes are listed below (for details, see Section 4.4):

- Selection of all electrodes (same as after changing the referencing scheme only).
- Selection of 14 electrodes, 10 of which are from Emotiv Epoc, and four of which substitute the missing ones.

- Selection of 10 electrodes having exact match with the Emotiv Epoc set.
- Selection of 10 electrodes, different from the Emotiv Epoc set.
- Selection of five electrodes resembling the Emotiv Insight set.
- Selection of five electrodes, different from the Emotiv Insight set.

The results of the detection on data with different electrode sets is shown in Figure 11. These results span in the range of 80-95% sensitivity and 2-5 FA/hour specificity, which is larger than the range for results after different emulation steps with standard parameters.

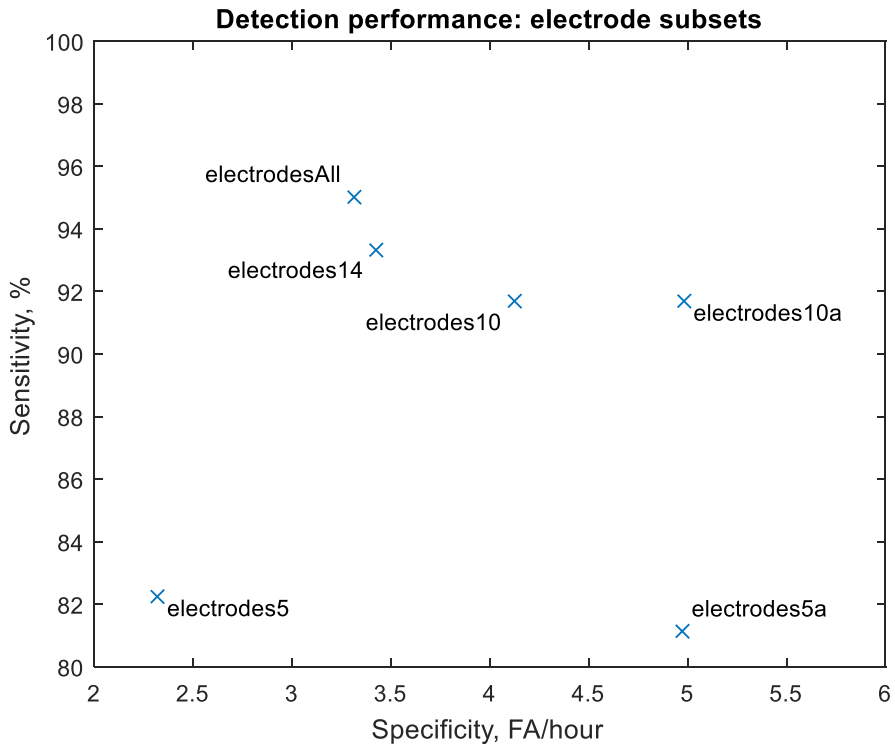


Figure 11. Evaluation of the detection performance after the selection of different sets of electrodes. Data emulation markers: `electrodesAll` – all electrodes taken; `electrodes14` – 14 electrodes, representing the full set of Emotiv Epoc electrodes; `electrodes10` – 10 electrodes with exact match with Emotiv Epoc set; `electrodes10a` – 10 electrodes, different from the Emotiv Epoc set; `electrodes5` – 5 electrodes, resambling Emotiv Insight set; `electrodes5a` – 5 electrodes, different from Emotiv Insight set.

The general tendency seems to be consistent. The best performance shows the selection of all electrodes (equal to the step changing the reference scheme). The next best selection is 14 electrodes, resembling the set of Emotiv Epoc electrodes. Two sets with 10 electrodes

give the next performance result and the two 5-electrode sets seem to result in the worst performance. Thus, the number of the electrodes in the set seem to have a direct impact on the detection. However, it is hard to make distinct conclusions without the behavior of the detector, represented in ROC-curves. The extent and the nature of differences between the results can vary, depending on the shape of those curves.

The choice of the electrodes seems to influence the detection performance as well. In both pairs of sets with 5 and 10 electrodes, the sensitivity stays almost the same. The specificity, in turn, has a significant difference within those pairs. For the 10-electrode sets, the one with the electrodes of Emotiv Epoc results in false alarm rate 20% lower than for non-Emotiv Epoc electrodes. 5-electrode set, resembling the set of Emotiv Insight, gives the false alarm rate approximately two times lower than that for non-Emotiv Insight set.

5.3.2 Sampling rate

The next emulation parameter that has been varied in this experiment is the targeting sampling rate of the data. Each sampling rate change was performed after the change in referencing and the selection of 10 electrodes of Emotiv Epoc (for details, see Section 4.5). The chosen rates are listed below:

- Sampling rate of 256 Hz (unchanged; equal to the step of selection of 10 Emotiv Epoc electrodes).
- Sampling rate of 192 Hz.
- Sampling rate of 128 Hz (an option of Emotiv Epoc).
- Sampling rate of 96 Hz.
- Sampling rate of 64 Hz.
- Sampling rate of 32 Hz.

The performance results of the detector on the data with differently changed sampling rate is presented in Figure 12. It can be seen, that lowering of the sampling rate to 32 Hz simplified the decision boundary of the detector to contain no seizure features at all (both sensitivity and false alarm rate values are zero). This result is the same as with random classifier. However, the behavior of the detector after changing the tradeoff between specificity and sensitivity is unknown and may outperform the random detection.

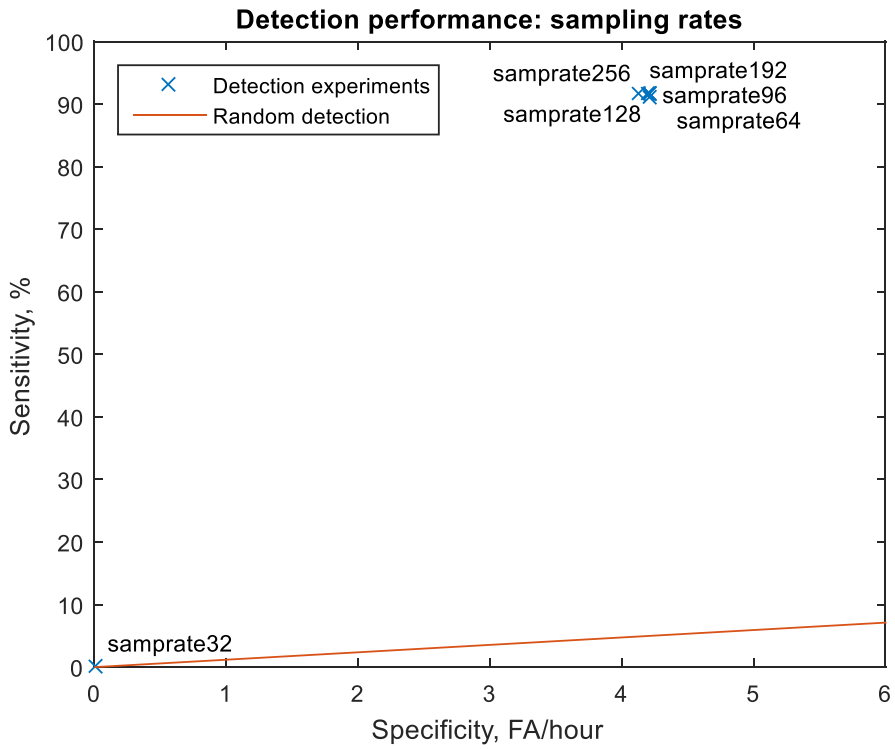


Figure 12. Evaluation of the detection performance after differently changing the sampling rate. The blue crosses represent experimental results. The red line represents the ROC-curve of random classifier. Data emulation markers: `samprateN` – lowering the sampling rate to N Hz.

The graph in Figure 12 shows the ROC-curve of the random classifier in the specificity range of 2-6 FA/hour. Its sensitivity does not exceed the value of 8%. This means, that any result, contained in the range of 80-100% sensitivity and 2-6 FA/hour false alarm rate, is vastly higher than random detection in terms of sensitivity as well (at least, by an order of magnitude).

The results of detection performance, achieved with the sampling rates starting from 64 Hz, are located compactly. The zoomed in version of the graph is given in Figure 13. In this standard comparison scale, the results seem to remain close to each other. They are enclosed by the range of 91-92% sensitivity and 4.0-4.3 FA/hour specificity. These variations seem small enough to consider them being caused by training variations. Thus, they will be assumed equal.

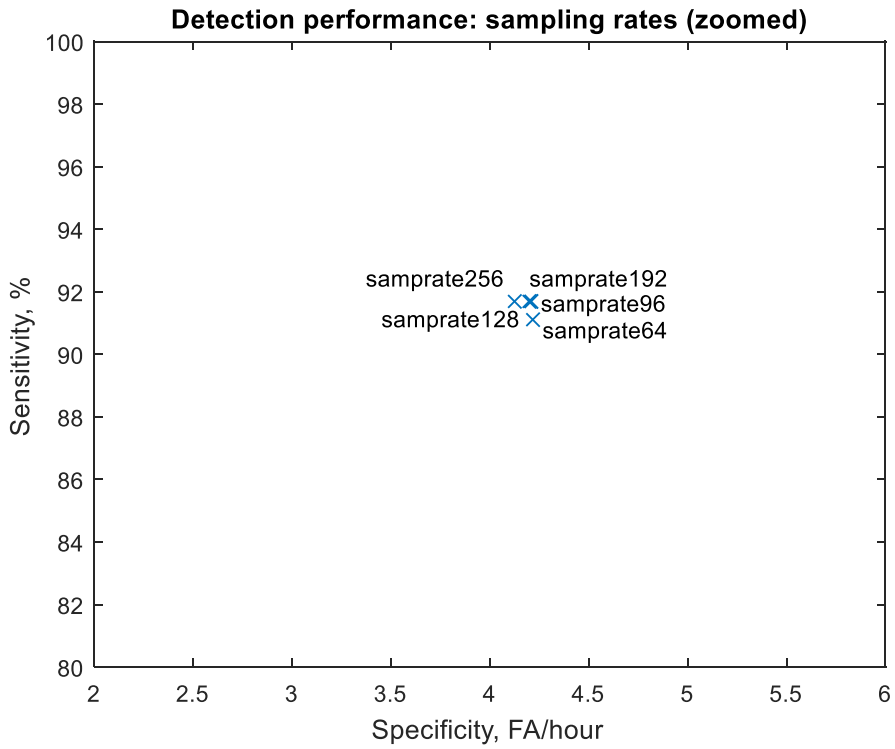


Figure 13. Evaluation of the detection performance after differently changing the sampling rate (zoomed). Data emulation markers: `samprateN` – lowering the sampling rate to N Hz.

5.3.3 Sample resolution

Sample resolution was an object to variation next in this experiment. Each change of the sample resolution was performed following the change in referencing, selecting a subset of 10 Emotiv Epoc electrodes and lowering the sampling rate to 128 Hz. The targeting resolutions are listed below (for details, see Section 4.6):

- Sample resolution of 16 bps (original sample resolution).
- Sample resolution of 14 bps (an option of Emotiv Epoc).
- Sample resolution of 12 bps.
- Sample resolution of 10 bps.
- Sample resolution of 8 bps.
- Sample resolution of 6 bps.

Figure 14 presents the results of detection for each of the mentioned emulations. The reduction in sample resolution up to 10 bps seems not to greatly decrease the detection capabilities

of the chosen algorithm. These results stay significantly better than random guessing. The selection of 8 bps reduces the performance to the level of random detection. Further reduction of the sample resolution to 6 bps leads to the performance, vastly worse than random detection (especially in terms of false alarm rate, which raises approximately 20 times).

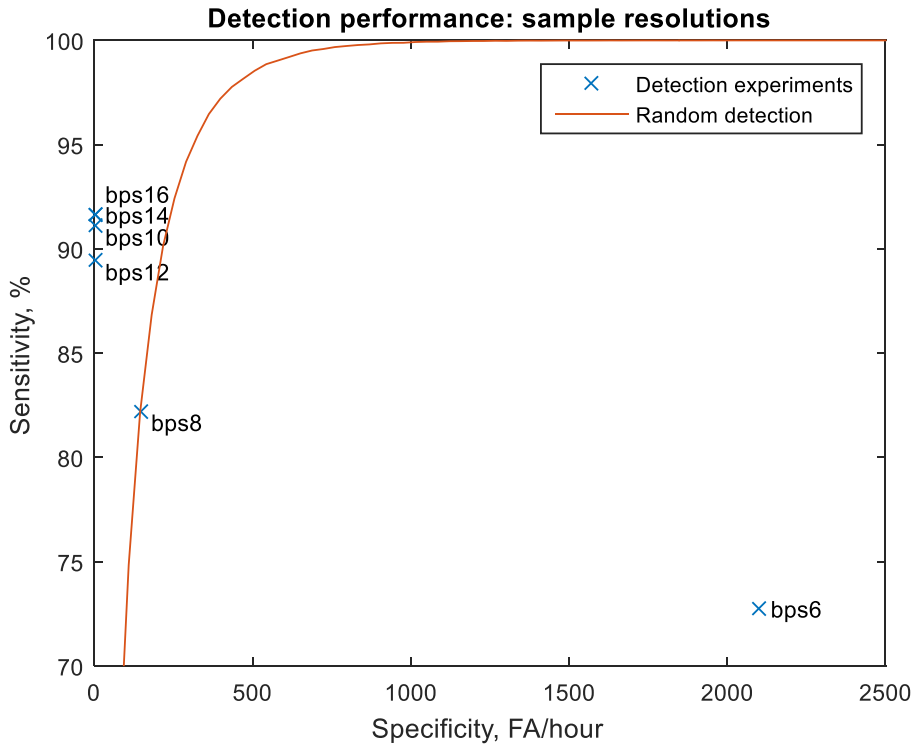


Figure 14. Evaluation of the detection performance after differently changing the sample resolution. The blue crosses represent experimental results. The red line represents the ROC-curve of random classifier. Data emulation markers: `bpsN` – lowering the sample resolution to N bps.

More experimentation is desirable to determine the behavior of the detector on the data with low sample resolution, when the tradeoff between sensitivity and specificity is varied. The confirmation of the non-outlier nature of the received results should also be performed. These results will be considered correct further in this work.

The same results are presented in the scale of 80-100% sensitivity and 2-6 FA/hour specificity in Figure 15. It can be seen, that the results up to 10 bps of sample resolution lie in the range of 4.0-4.5 FA/hour false alarm rate and 89-92% sensitivity. Since that range is relatively small, the impact of sample resolution reduction might be considered little.

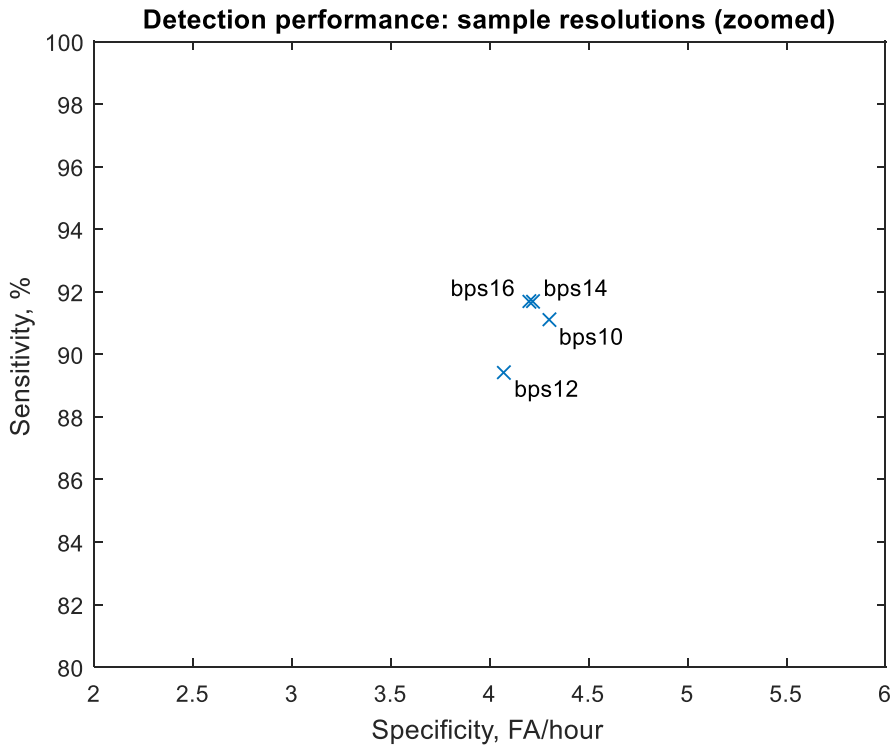


Figure 15. Evaluation of the detection performance after differently changing the sample resolution (zoomed). Data emulation markers: `bpsN` – lowering the sample resolution to N bps.

Results for 16 bps and 14 bps are practically equal, while reduction to 10 bps seems to degrade the performance slightly. Result for 12 bps of sample resolution has a tradeoff between the sensitivity and specificity, so the exact relation to other results is hard to judge with the lack of ROC-curves. However, increase in the performance after decreasing the sample resolution from 12 bps to 10 bps seems to be controversial. Thus, these results will be considered approximately equal. The overall variance in the described results is also small enough to consider it to have the probable cause in the training variations.

5.3.4 Noise levels

The last emulation parameter to variate in this experiment was the level of the noise. The noise was added to the signals prior to other emulation steps, which include changing the referencing scheme, selecting the 10 electrodes from Emotiv Epoc, reducing the sampling rate to 128 Hz and decreasing the sample resolution to 14 bps. Different parameters of the white Gaussian noise power, used in this experiment, are given below (for details, see Section 4.7):

- Noise power of 0 dB (no noise, equal to the step of lowering sample resolution to 14 bps).
- Noise power of 5 dB.
- Noise power of 10 dB.
- Noise power of 15 dB.
- Noise power of 20 dB (noise used for emulating Emotiv Epoc device).
- Noise power of 25 dB.
- Noise power of 30 dB.
- Noise power of 35 dB.
- Noise power of 40 dB.
- Noise power of 45 dB.
- Noise power of 50 dB.
- Noise power of 60 dB.

The results of the detection after the introduction of different noise are presented in Figure 16. The overall range, covering these results, is 28-92% of sensitivity and 0-6 FA/hour of specificity. All of these results are better, than random detection. No high variance can be observed in the results up to the noise level of 30 dB. The results with 35 dB and 40 dB of noise are poorer than with weaker noise.

Further increase in noise level lowers both sensitivity and false alarm rate, which, in general, might mean the tradeoff between the sensitivity and specificity. Nevertheless, it seems to be consistent to think, that the increase in noise level should not lead to the raise in the detection quality. Thus, these results will be considered at least not greater than with the noise below 45 dB. Construction of the ROC-curves might reveal the specific relation between those results.

The results zoomed to the range of 80-100% sensitivity and 2-6 FA/hour specificity are demonstrated in Figure 17. The performance on the data with noise up to 30 dB is enclosed in the range of 90-92% sensitivity and 4.0-4.3 FA/hour of specificity (4-6 FA/hour, if the result with 35 dB noise is included). This relatively low variation in the results can be have the source in the variations of the training process or the random nature of the noise. This assumption will be considered true further in this work.

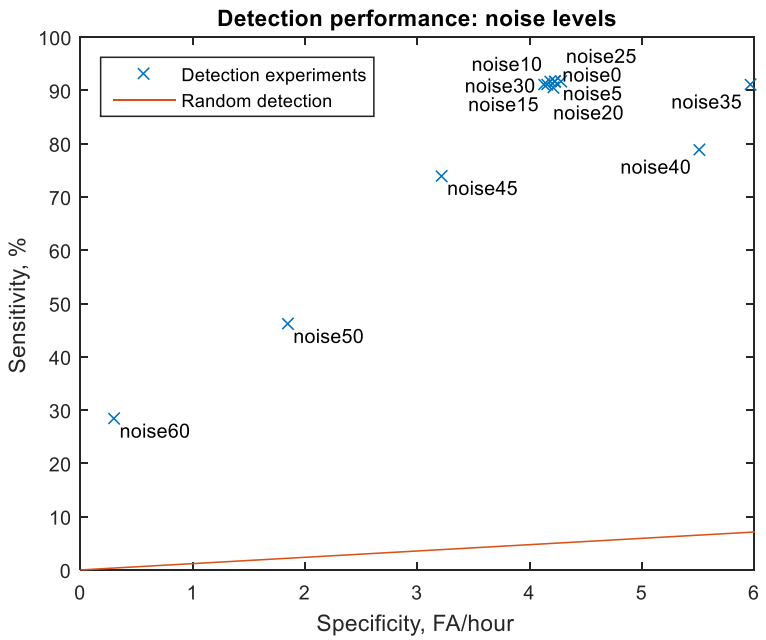


Figure 16. Evaluation of the detection performance after adding the white Gaussian noise with different power parameter. The blue crosses represent experimental results. The red line represents the ROC-curve of random classifier. Data emulation markers: `noiseN` – adding the noise with the power parameter of N dB.

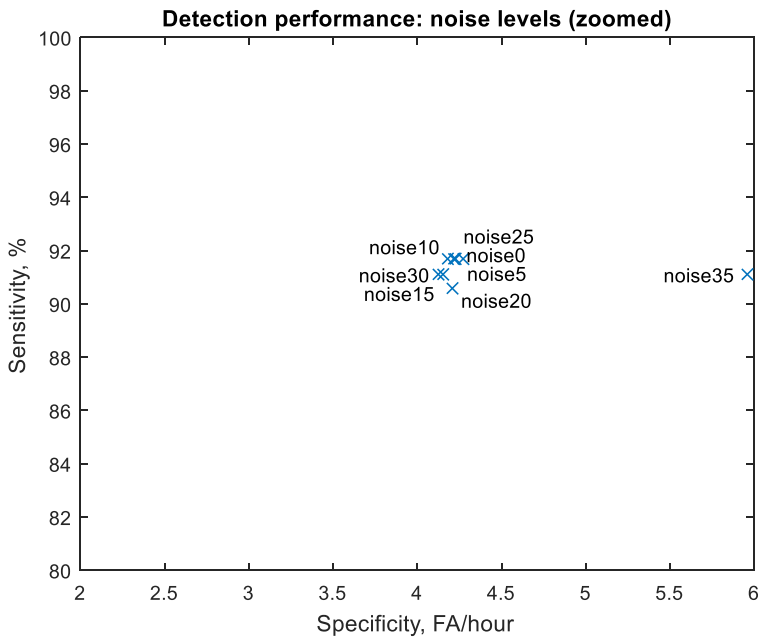


Figure 17. Evaluation of the detection performance after adding the white Gaussian noise with different power parameter. Data emulation markers: `noiseN` – adding the noise with the power parameter of N dB.

6 DISCUSSION AND FUTURE WORK

6.1 Discussion of results

6.1.1 Comparison of impacts of emulation steps

Decreasing of the characteristics of the EEG acquisition device to the parameters of the Emotiv Epoc headband does not seem to cause a critical drop in the capabilities of the chosen algorithm to detect epileptic seizures. The little influence of the changes in the referencing scheme can be explained by the nature of the transformation, performed on this step. The output channels constitute a linear combination of the input channels. Thus, the information should not be lost on this step.

The reduction of the number of electrodes to the set of 10 electrodes of Emotiv Epoc leads to the direct loss of information from the omitted channels. Although the impact is not strong, for some patients it might be, due to the character of the spatial appearance of their seizures (the significance of the selection of electrode subsets will be discussed in Section 6.1.2).

Effects of other emulation steps, performed with the parameters of Emotiv Epoc, does not seem to change the detection results significantly. Thus, the characteristics of Emotiv Epoc can be considered enough for enabling acceptable detection of epileptic seizures. The effects might change, though, if another detection algorithm would be evaluated in the similar experiments. The nature of information, extracted from the data by other methods, might be disturbed by the characteristics, considered in this work. The effects of the emulation steps will be discussed in more details in further sections.

6.1.2 Impact of the electrode subset selection

The results, demonstrated in Section 5, show, that the most influential parameter of the data acquisition system seems to be the set of the electrodes utilized. The number of the electrodes defines the spatial coverage of EEG acquisition. It seems to have a direct impact on the performance of detection of epileptic seizures by the chosen algorithm. The choice of the electrode positions seems to be also important.

These effects can be explained by the variability of the spatial appearance of seizures between patients. On the one hand, the detector may benefit from the high spatial coverage for some patients, since their seizures have a wide spread. On the other hand, for other patients, the coverage is less important, since the seizures appear more localized. The presence of the electrodes in some specific locations is of higher importance in such cases.

In a sense of the selection of the device properties, there are two options for electrode subsets. One option is to utilize always a large number of electrodes with high spatial coverage. In that case, the device would be universal and would be able to perform well with most of the patients. Another option is to incorporate different smaller sets of electrodes in various devices. The patient-specific selection of the device then would be required, as well as the preliminary testing, in order to choose electrode positioning according to the seizure appearance.

The reduction of the number of channels may be beneficial for the mobile system. Minimization of the amount of the acquired data allows decreasing expenses on the data transmission and storage, as well as on the processing time in most cases. Consequently, the battery usage of the mobile devices, incorporated in the system, might be also prolonged.

6.1.3 Impact of sampling rate

The sampling rate seems to have the least influence on the detector performance in the range 64-256 Hz. The difference in the results between evaluations can be caused by the variations in the training procedure of the classifier. Only with the parameter value of 32 Hz, the detector shows an abrupt reduction in performance.

The mentioned effects can be explained by the essence of the features, used in the detection algorithm. They encode the spectral information of different channels in multiple time points. Since the information is used only from the band of 0-24 Hz, as is advised by the author of the algorithm, there should no change in the extracted features, if the data is to be transformed in other spectral bands.

Reduction of the sampling rate, in turn, decreases the number of higher frequencies that would be preserved in the signal representation. The highest frequency encoded has a value of the half of the sampling rate of the data. Hence, for the sampling rates starting from 64 Hz,

the frequencies of 32 Hz and higher are included in the signal, and the band of interest is available for feature extraction. In general, the minimal spectral information should be preserved up to the sampling rate of 48 Hz. For the parameter of sampling rate equal to 32 Hz, the maximal frequency preserved is 16 Hz, meaning that the desired spectral band 0-24 Hz becomes disturbed.

The stability of the epilepsy detection algorithms to the changes of the sampling rate of data depend on the spectral band, which they utilize, directly or indirectly. Thus, the conclusions made here cannot be directly generalized on the set of all the detectors. Separate considerations and probably experimentation for each detector are needed.

The reduction of the sampling rate of the devices might also be beneficial in the development of the mobile system. The sampling rate defines the number of samples, acquired in time, and therefore the amount of data needed to be stored, transferred and processed. The consequences are the same, as with the data volume reduction by limiting the number of channels utilized.

6.1.4 Impact of sample resolution and noise level

Varying of both the sample resolution and the level of additive white Gaussian noise has a relatively little influence on the performance of the detector in a certain range of values. Since the quantization errors can be modeled as addition of white noise to the signal [24], the effects of the reduction of sample resolution and of the introduction of additional noise can be discussed together.

Addition of the white noise to the signal effectively results in the addition of a constant value to the energetic spectrum on all frequencies. Since the noise is random, the exact values added to different frequencies may vary from each other and between the model evaluations.

However, the features, extracted from the energetic spectrum in this work, have a cumulative nature. They summarize energies of the sub-bands of 0-24 Hz spectral band. This means, that the variation in the exact values, added to the spectral frequencies, will be averaged. Thus, addition of the white noise results in shifting of the feature vectors by some constant, equal for all the features, representing different sub-bands. Essentially, even if the noise would have not the flat distribution, but the same throughout all the experimentation, all the

features, extracted from different fragments of data, would be shifted in the feature space the same way, affecting only the positioning of the decision boundary, but not its shape.

The classifier, used in the implementations of experiments in this work, was not set up to normalize the features it receives as an input for training. Hence, it can tolerate only a certain shifting of the feature vectors in the feature space. Introduction of the normalization step might increase the stability of the classifier to the white noise.

It should be noted, that very high noise levels could affect the results, even if the classifier would be able to tolerate the shifts in feature space. Even though the feature extractor accumulates the random energy values within the sub-bands, some random difference between the resulting shifting values exist. If the noise has high power, the impact of these random shifting variances might be high enough to influence the distribution of the features in the feature space, making the separation of classes more difficult or even impossible.

The property of the detector to be able to tolerate the noise, introduced to the signal might be beneficial in the development of mobile systems. It allows reducing the expenses on the quality of acquisition devices. Moreover, the sample resolution affects the volume of data acquired, decreasing of which has benefits, discussed above in the cases of reduction of the number of channels and lowering of the sampling rate.

6.2 Future work

The thorough experimentation was restricted in this work by the technical limitations. They arose mostly from the computational heaviness of the conducted experiments. The bottleneck of the computations was the process of training an SVM classifier. It has been repeated numerous times for each testing record of each times. Thus, attention should be paid to the classifier implementation choice, if the further research with data parameters emulations is to be conducted. The ways to optimize that part of the computations might be to utilize optimized CPU or GPU version of the classifier with carefully selected parameters.

Faster computations would allow construction of ROC-curves, which require multiple retraining of the classifier with the variation of some internal parameter. This parameter could be the relative cost of misclassifications. ROC-curves would enable conduction of thorough comparison analysis of any results, disambiguating difficult cases. The conclusions, made

from such analysis would be more justified. Faster detector training could also allow multiple result evaluations with the same set of parameters, thus collecting the statistics on the variations in the training procedure.

One of the directions of the future work can be devoted to consideration of various emulation steps. First, comparing of different variations of referencing schemes and referencing electrodes might be beneficial. Other types of signal distortions could be tested. These distortions can be inspired by the effects of wearing of headbands in real life, such as occasional electrode detachments or decrease in contact quality. The mentioned distortions can be emulated by zeroing portions of the signals, lowering of their amplitude or introducing additional noise.

Another direction of the research can be the consideration of different detection algorithms, used for the evaluations of the detection performance. Generalization of the effects of several characteristic changes might become consequently possible. The algorithms can differ in the detection schemes utilized, classifier chosen or features extracted from signals. Utilization of other clinical datasets as the basis for emulations might also increase the generalization properties of the conclusions.

Finally, the collection of real epileptic data using various commercial EEG headbands should allow the verification of the results, achieved through the emulations. The real data might inspire other models for emulation of the switching between data acquisition devices. In addition, the datasets of signals, acquired with the equipment with the potential to be used in the mobile closed-loop system, would enable a research, devoted to the selection of the detection algorithm, incorporated in such a system. The research would involve testing of different existing algorithms, tuning their parameters or developing a new one.

7 CONCLUSIONS

The aim of this research was to estimate the potential to use commercial EEG headbands for the detection of epileptic seizures. Data from the commercial headsets was emulated by transforming the characteristics of the clinical data. The changes in the detection performance of an existing algorithm were evaluated after emulations with different parameters. The characteristics, considered in this work, were the referencing scheme, the subset of utilized electrodes, the sampling rate, the sample resolution and the level of additional noise.

The results of the research showed, that the capabilities of the chosen method to detect seizures have not critically dropped after the emulations towards the characteristics of Emotiv Epoc device. This gives a positive estimate of the potential for usage of that and other commercial devices in the epilepsy detection problem and for incorporating them into the mobile closed-loop system.

The work also revealed, that the range of the values of device parameters exist, which can be tolerated by the detection algorithms. This range can be taken into account in the process of selecting suitable commercial devices, or if new specialized equipment for acquisition of EEG signals in context of epilepsy is to be designed.

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