

1 Seizure Detection using EEG and ECG Signals for Computer-based 2 Monitoring, Analysis and Management of Epileptic Patients

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13
14 **Abstract:** In this paper a seizure detector using EEG and ECG signals, as a module of a
15 healthcare system, is presented. Specifically, the module is based on short-time analysis with time-
16 domain and frequency-domain features and classification using support vector machines. The seizure
17 detection module was evaluated on three subjects with diagnosed idiopathic generalized epilepsy
18 manifested with absences. The achieved seizure detection accuracy was approximately 90% for all
19 evaluated subjects. Feature ranking investigation and evaluation of the seizure detection module using
20 subsets of features showed that the feature vector composed of approximately the 65%-best ranked
21 parameters provides a good trade-off between computational demands and accuracy. This configurable
22 architecture allows the seizure detection module to operate as part of a healthcare system in offline
23 mode as well as in online mode, where real-time performance is needed.

24
25 **Keywords:** Seizure, electroencephalogram, electrocardiogram, support vector machines.

26 27 1. Introduction

28 More than fifty million people worldwide, approximately 1% of the world population, suffer
29 from epilepsy, which is the third most common neurological disorder in the United States after
30 Alzheimer's disease and cerebrovascular events (Hauser, 1997). Moreover, more than 30% of the

1 epileptic patients suffer from seizures that are refractory to medication (Kwan & Brodie, 2000).
2 Epilepsy can directly influence patients' quality of life because of treatment-related side effects,
3 cognitive and particularly memory dysfunction or injuries associated to seizures, potential psychiatric
4 co-morbidities and social isolation due to stigma, especially when it runs as a long term disease
5 (Bergley et al., 2000a). Moreover, there are indications that the members of the family or the caregivers
6 of patients are also experiencing multiple psychological or social difficulties in the form of depression
7 and social restriction (Ellis et al., 2000). Apart from these negative effects to personal and social
8 parameters of life, the high annual budget spent for the healthcare activities related to the cost of
9 investigation, treatment and hospitalization of epileptic patients cannot be disregarded (Ali et al., 2014;
10 Bergley et al., 2000b; Hunyadi et al., 2012). The highly negative socioeconomic impact of epilepsy
11 justifies the need for further investigation and development of technology-supported diagnostic and
12 therapeutic systems.

13 This disease is manifested through recurrent epileptic seizures, resulting from an abnormal
14 synchronous activity in the brain involving a large network of neurons (Valderrama et al., 2010; Le
15 Van Quyen et al., 2005). The epileptic seizures are not randomly occurring events but they are instead
16 the product of highly non-linear dynamics in the brain circuits evolving over time (Corsini et al., 2006).
17 The underlying process of seizures occurrence is not completely understood yet, thus making their
18 study and prediction a difficult task (Corsini et al., 2006; Mohseni et al., 2006).

19 The progress of technology over the last decades has provided the means for shifting from
20 qualitative to quantitative clues, related to the unknown process that produces a seizure. Seizure
21 investigation is mainly performed with quantitative analysis of the electroencephalogram (EEG)
22 (Valderrama et al., 2010; Nasehi & Pourghassem, 2012; Tong & Thankor, 2009; Gotman, 1982). The
23 detection of epileptic seizures is based on visual analysis of the multidimensional EEG signal (typically
24 consisting of time-synchronous recordings captured from a 10-20 scalp electrodes system), which is
25 performed manually by expert neurologists for the detection of patterns of interest such as spikes or
26 spike wave complexes (Mohseni et al., 2006). This procedure is tedious, time-consuming (especially
27 for long time recordings) and expensive since investigation from experts is needed. Furthermore, as
28 there are many different patterns of clinical and electrophysiological seizure manifestation, the
29 elaborative investigation of ictal or interictal patterns becomes demanding and complex.

1 Apart from the EEG, the study of electrocardiographic (ECG) signals can also offer valuable
2 information related to the seizure discharges (Valderrama et al., 2010; Mithin et al., 2012). It has been
3 shown that seizures are often associated with cardiovascular and respiratory alterations such as
4 tachycardia (Valderrama et al., 2010; Nasehi & Pourghassem, 2012; Valderrama et al., 2012; Greene et
5 al., 2007; Varon et al., 2013; Zijlmans et al., 2002). Specifically, measures related to the heart rate (e.g.
6 mean heart rate, heart rate variability and acceleration) (Valderrama et al., 2010; Nasehi &
7 Pourghassem, 2012; Mithin et al., 2012; Valderrama et al., 2012; Leutmezer et al., 2003), as well as the
8 respiration rate (Greene et al., 2007), are known to be valuable clinical signs of early manifestation of
9 an epileptic discharge. Besides the heart-rate based characteristics, the morphology of the ECG signal
10 is related to seizures (Varon et al., 2013). Significant changes in ECG signal characteristics indicate the
11 need for detailed investigation of the corresponding interval of an EEG recording or may be the cause
12 for an alert for a possible seizure.

13 The subjective evaluation of biosignals, such as EEG and ECG, makes automatically extracted
14 parameters (computer-based) highly useful for diagnostics. Moreover, due to the difficulty of visual
15 investigation of multiparametric recordings (in this case time-synchronous EEG and ECG) and in
16 combination with the progress of signal processing and pattern recognition technology, many
17 approaches for automatic detection of seizures have been proposed in the literature.

18 The general structure of the proposed in the literature methodologies for seizure detection
19 consists of pre-processing, feature extraction and classification. During pre-processing the
20 multiparametric recordings (i.e. the EEG and ECG signals) are divided in frames of constant length,
21 called epochs, on which normalization and/or filtering are optionally applied. In the feature extraction
22 step a parametric feature vector is extracted from each epoch, while in the classification stage each
23 epoch's feature vector is labeled either as seizure or as clear (i.e. non-seizure). The seizure detection
24 model can be either subject-dependent or subject-independent, as well as based either on EEG signal
25 analysis or on EEG and ECG signal analysis (Hunyadi et al., 2012; Valderrama et al., 2010; Nasehi &
26 Pourghassem, 2012; Greene et al., 2007).

27 In most of the parametric approaches found in the literature the analysis is based on the
28 estimation of the EEG channels' spectral magnitude (Valderrama et al., 2010; Mohseni et al., 2006;
29 Nasehi & Pourghassem, 2012; Greene et al., 2007). Other EEG features that have been reported are the
30 autoregressive filter coefficients, the continuous and discrete wavelet transform, the energy per brain

1 wave (delta, theta, alpha, beta, gamma) bands (Valderrama et al., 2010; Nasehi & Pourghassem, 2012;
2 Ocak, 2009; Tong & Thankor, 2009; Chen, 2014), band-pass based features (Tang & Durand, 2012),
3 entropy (Gandhi et al. 2012; Kumar et al., 2010; Ocak, 2009) and phase space representation (Sharma
4 & Pachori, 2015). In addition, time domain features have been proposed, such as zero-crossing rate
5 (Hunyadi et al., 2012) and temporal statistics of the EEG signal amplitude per channel (Valderrama et
6 al., 2010; Nasehi & Pourghassem, 2012). The ECG features are mainly based on the heart rate
7 estimation (based on R-R intervals (Sabarimalai et al., 2012)) and its statistical measures , i.e. heart
8 rate variability (Valderrama et al., 2010; Nasehi & Pourghassem, 2012; Corsini et al., 2006; Greene et
9 al., 2007; Varon et al., 2013; Zijlmans et al., 2002). Features describing the morphology of the ECG
10 waveforms by means of principal component analysis have also been used (Varon et al., 2013).

11 For the classification of the parameterized epochs several powerful machine learning algorithms
12 have been reported. The most widely used are the artificial neural networks (Mohseni et al., 2006;
13 Nasehi & Pourghassem, 2012; Kumar et al., 2010; Gulera et al., 2005; Kiyimika et al., 2004; Subasi et
14 al., 2005; Gandhi et al., 2012) and the support vector machines (Sharma & Pachori, 2015; Hunyadi et
15 al., 2012; Tang & Durand, 2012; Zavar et al., 2011; Valderrama et al., 2010; Shoeb et al., 2004; Shoeb
16 & Gutttag, 2010). Other algorithms that have been evaluated are the k-means clustering (Varon et al.,
17 2013), the k-nearest neighbors (Chen, 2014; Tzallas et al., 2009; Wang et al., 2011), the linear
18 discriminant analysis (Greene et al., 2007; Liang et al., 2010), the fuzzy logic (Fazle Rabbi & Fazel-
19 Rezai, 2012; Aarabi et al., 2009), the singular value decomposition (Hassanpour et al., 2004),the
20 decision trees (Polat & Gunes, 2007; Polat & Gunes, 2008; Tzallas et al., 2009) and the Gaussian
21 mixture models (Chua et al., 2008).

22 In this article we evaluate a large scale set of time-domain and frequency-domain EEG and ECG
23 features for seizure detection, which are popular in the literature for brain and heart statistical signal
24 processing, respectively, as part of a module implementation in a monitoring system for e-Health.
25 Furthermore, we investigate the effect on the module's performance when using subsets of these
26 features, with respect to a feature ranking evaluation, in order to develop online (real-time) and offline
27 versions of it. This evaluation is part of ongoing work for constructing tools (online and offline) for
28 seizure detection and analysis for the needs of the ARMOR project (ARMOR).

29 The rest of this paper is organized as follows: In Section 2 we present the concept of the
30 ARMOR framework and explain the purpose of seizure detection in it. Section 3 presents the proposed

1 architecture for seizure detection from EEG and ECG signals. In Section 4 we describe the
2 experimental setup and in Section 5 the evaluation results. Finally in Section 6 we conclude this work.

3

4 **2. The ARMOR framework**

5 The seizure detection architecture presented in the following section is part of the ARMOR
6 framework for monitoring, analysis and management of epileptic patients and in general brain
7 disorders, which is part of the EC FP7 research and development ARMOR project (ARMOR). The
8 concept of the ARMOR framework is illustrated in Figure 1.

9

10 **Figure 1.** The concept of the ARMOR framework.

11

12 Within the ARMOR framework patients suffering from seizures are monitored through a number
13 of different sensors (using a wearable solution) and the acquired multimodal data (including EEG,
14 ECG, EMG and EOG recordings) are wirelessly transmitted to the home gateway. The role of the home
15 gateway is twofold: Firstly, the transmitted multimodal data are time-synchronized and afterwards
16 processed in real time (online analysis) in order to detect potential seizures (in general brain
17 abnormalities) and send an alarm (email, sms, emergency call) to the patient's family, doctors and/or
18 medical supportive staff, which will provide the required first aid and medical support. Secondly, the
19 data are sent for permanent storage to a database; and the offline analysis is performed there by
20 neuroscientists in order to discover patterns, motifs and associations related to seizures and then
21 reconfiguration of the ARMOR system for specific patients follows (decision making). In an online
22 analysis setting, the trade-off between seizure detection performance and computational load for real-
23 time operation is important to be investigated, while during the offline analysis the target is the
24 maximum performance of the seizure detection algorithm.

25

26 **3. Module for Online Seizure Detection from EEG-ECG Recordings**

27 In the presented module for seizure detection only the EEG and ECG recordings are used from the
28 multimodal recorded data. The EEG and ECG data have been proven to be very important for analysis
29 of seizures in previous studies, while EMG and EOG have mainly been used for movement and artifact

1 detection, and thus are not part of this study. The block diagram of the seizure detection module
 2 adopted in this study is illustrated in Figure 2.

3

4 **Figure 2.** Block diagram of the EEG-ECG based online seizure detection module.

5

6 We assume that the data captured from the $N + 1$ sensors (where N are the EEG electrodes plus
 7 one ECG channel) have been synchronized and transmitted as streams of multidimensional signals.
 8 Thus, the input to the illustrated in Figure 2 module consists of time-synchronous streams of EEG and
 9 ECG signal samples. As shown in Figure 2, in a first step the EEG, $x_{EEG} \in \mathbb{R}^N$, and ECG, $x_{ECG} \in \mathbb{R}$,
 10 signals are preprocessed. Preprocessing consists of frame blocking of the incoming streams to epochs
 11 of constant length w with constant time-shift s . Each epoch is a $(N + 1) \times (w)$ matrix, where N is
 12 the number of EEG electrodes and $N + 1$ is the N -dimensional EEG signal appended by the ECG
 13 signal.

14 After preprocessing the extracted epochs are in parallel processed by time-domain and frequency-
 15 domain feature extraction algorithms individually for the N -dimensional EEG and the 1-dimensional
 16 ECG signals. In particular, each of the N -dimensions of the EEG signal are processed by time-domain
 17 and frequency-domain feature extraction algorithms for EEG, while the ECG signal is processed by
 18 time-domain feature extraction algorithms (based on heart rate estimation) dedicated for
 19 electrocardiogram, as shown in the block diagram of Figure 2. The extracted time-domain and
 20 frequency-domain features for the EEG, $T_{EEG}^i \in \mathbb{R}^{|T_{EEG}|}$ and $F_{EEG}^i \in \mathbb{R}^{|F_{EEG}|}$, with $1 \leq i \leq N$, and the
 21 ECG signal, $T_{ECG} \in \mathbb{R}^{|T_{ECG}|}$, are afterwards concatenated to a single feature vector
 22 $V \in \mathbb{R}^{N(|T_{EEG}|+|F_{EEG}|)+|T_{ECG}|}$ representing each epoch, as shown in Figure 2. The extracted sequences of
 23 feature vectors, V , are short-time parametric representations of the EEG and ECG signals representing
 24 the time and spectral characteristics of the multimodal signals. This sequence of feature vectors is
 25 afterwards used as input to a classification model which assigns a class label (seizure class or non-
 26 seizure class) to each of the vectors, i.e. to the corresponding time-intervals (epoch).

27 During pre-processing the time-synchronized EEG and ECG recordings were frame blocked to
 28 epochs of 1 second length, without time-overlap between successive epochs. For each epoch time-

1 domain and frequency domain features were extracted separately for each of the 21 EEG channels and
 2 the ECG channel. In particular, each of the EEG channels was parameterized using the following
 3 features: (i) time-domain features: minimum value, maximum value, mean, variance, standard
 4 deviation, percentiles (25%, 50%-median and 75%), interquartile range, mean absolute deviation,
 5 range, skewness, kurtosis, energy, Shannon's entropy, logarithmic energy entropy, number of positive
 6 and negative peaks, zero-crossing rate, and (ii) frequency-domain features: 6-th order autoregressive-
 7 filter (AR) coefficients, power spectral density, frequency with maximum and minimum amplitude,
 8 spectral entropy, delta-theta-alpha-beta-gamma band energy, discrete wavelet transform coefficients
 9 with mother wavelet function Daubechies 16 and decomposition level equal to 8, thus resulting to a
 10 feature vector of dimensionality equal to 55 for each of the 21 EEG channels, i.e. 1155 EEG features in
 11 total.

12 The ECG channel was parameterized using the following features: the heart rate absolute value
 13 and variability statistics of the heart rate, i.e. minimum value, maximum value, mean, variance,
 14 standard deviation, percentiles (25%, 50%-median and 75%), interquartile range, mean absolute
 15 deviation, range, thus resulting to a feature vector of dimensionality equal to 12. The heart rate
 16 estimation was based on Shannon energy envelope estimation for R-peak detection algorithm,
 17 implemented as in (Sabarimalai et al., 2012). The dimensionality of the overall feature vector V is
 18 $1155+12=1167$.

19 During the training phase of the seizure detector, a dataset of feature vectors with known class
 20 labels (labeled manually by medical experts) is used to train a binary model M (two classes: seizure
 21 vs. non-seizure) using a classification algorithm f . At the test phase the trained seizure model, M , is
 22 used in order to assign to each epoch's feature vector, V , the corresponding class using the same
 23 classification algorithm, f , as in the training phase. Thus, for each epoch i a binary label d_i , i.e.
 24 seizure or not, is determined as:

$$25 \quad d_i = f(V_i, M) \quad (1)$$

26 and the sequence of incoming EEG-ECG data is decomposed to time-intervals of seizure or clear (non-
 27 seizure) recordings. Post-processing of the automatically classified labels can be performed to improve
 28 the performance of the module.

1 The above described module for seizure detection is part of the ARMOR framework as described
2 in Section 2, i.e. within the online and the offline analysis components. The modular architecture of the
3 ARMOR framework allows different configurations and setups in these two components, in order to
4 meet the requirements, i.e. real-time operation and maximum accuracy performance, respectively. In
5 the following, we evaluate the seizure detection module in online and offline scenarios.

7 **4. Experimental Setup**

8 The module for seizure detection described in the previous section was evaluated on data
9 collected within the ARMOR project. Specifically, data from 3 patients with diagnosed idiopathic
10 generalized epilepsy manifested with absences were collected in the Epilepsy Clinic in the Department
11 of Clinical Neurophysiology of St Thomas Hospital. The patients had a sleep video EEG after partial
12 sleep deprivation, with extended, prolonged recording on awakening and with one or multiple trial of
13 activation with hyperventilation. All three patients had one or more clinical events of absences during
14 the recordings that were captured by the video EEG. The electroencephalographic (21 electrodes: C3,
15 C4, Cz, F3, F4, F7, F8, Fp1, Fp2, Fz, O1, O2, P3, P4, Pz, T1, T2, T3, T4, T5, T6) and
16 electrocardiographic data were recorded with sampling frequency equal to 500 Hz. The recordings
17 were manually annotated to labeled intervals of interest by neurology experts of the King College
18 London. An example of a generalized epilepsy event together with the onset and offset time-stamps is
19 shown in Figure 3. All data were stored in EDF+ formatted files (Kemp & Olivan, 2003).

21 **Figure 3.** Example of EEG (in blue lines) and ECG (in black line) recordings together with manual
22 annotations of the seizure onset and offset times.

24 The computed feature vectors V , one for each EEG-ECG epoch were used to train binary seizure
25 detection models, M . In order to avoid the curse of dimensionality (Burges, 1998) we relied on the
26 support vector machines data-mining algorithm, implemented with the sequential minimal optimization
27 method (Keerthi et al., 2001) and polynomial kernel function. The binary seizure detection model was
28 implemented using the WEKA machine learning toolkit software (Witten & Frank, 2005).

29 During the test phase, the EEG and ECG recordings are pre-processed and parameterized as in
30 training. The SVM seizure detection model, M , is used to label each of the incoming EEG-ECG

1 epochs as seizure or clear (non-seizure). In the present evaluation no post-processing algorithm was
2 applied on the estimated epoch-based results.

3

4 **5. Experimental Results**

5 The seizure detection module presented in Section 3 was evaluated following the experimental
6 setup described in Section 4. The recordings acquired from three subjects (subject 07, subject 08 and
7 subject 09) were used for evaluating subject-dependent seizure detection models, i.e. the evaluated
8 training and test data subsets consisted of one subject in each experiment. In order to avoid overlap
9 between the training and the test data a ten-fold cross validation protocol was followed.

10 The confusion matrices for the SVM-based seizure detection models for the subjects 07, 08 and
11 09 are shown in Tables 1, 2 and 3, respectively. The accuracies are presented in percentages and the
12 non-seizure state is denoted as clear.

13

14 **Table 1. Seizure detection confusion matrix for subject 07**

15

16 **Table 2. Seizure detection confusion matrix for subject 08**

17

18 **Table 3. Seizure detection confusion matrix for subject 09**

19

20 As seen in the confusion matrices, the accuracy of detection of seizure varies from 92.31% (for
21 subject 07) to 77.78% (for subject 07), while the detection of clear intervals, i.e. interval recordings
22 without the presence of seizure, was found to be at least 99.24% for all three subjects. This variation in
23 the accuracy of the seizure detection epochs (approximately 21%), compared to the more robust
24 detection of non-seizure epochs (with variation of approximately 0.7%), is mainly owed to the limited
25 amount of training data which does not allow the SVM algorithm to model the seizure characteristics
26 with absolute performance. It is worth mentioning that the duration of each idiopathic generalized
27 seizure occurrence was approximately 2 up to 4 successive epochs, while the available seizure
28 occurrences for subject 08 were significantly fewer than the ones of subject 07, which presented the
29 best seizure detection performance.

1 Seizure detection performance is also assessed in terms of accuracy, precision and recall, defined
2 as:

$$3 \quad accuracy = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$4 \quad precision = \frac{TP}{TP + FP} \quad (3)$$

$$5 \quad recall = \frac{TP}{TP + FN} \quad (4)$$

6 where true positives are denoted as TP, true negatives as TN, false positives as FP and false negatives
7 as FN. Here we assume seizure class as positive and clear (non-seizure) class as negative. The results
8 for the three evaluated subjects, 07, 08 and 09, are shown in Table 4.

9

10 **Table 4. Seizure detection performance for all evaluated subjects in terms of accuracy, precision**
11 **and recall.**

12

13 As shown in Table 4, the overall accuracy of seizure detection for the subjects 07 and 09 is above
14 90%, while for subject 08 is almost 90%. The recall metric (or sensitivity), i.e. the fraction of relevant
15 instances that are retrieved for all three subjects, is more than 99%. Although direct comparison with
16 other studies is not possible due to the different specifications of each dataset, the achieved seizure
17 recognition accuracy is competitive to the performance reported in the literature, which in most
18 experimental setups varies from 80% to 95% (Shoeb et al., 2004; Mohseni et al., 2006; Nasehi &
19 Pourghassem, 2012; Greene et al., 2007).

20 In a further step we examined the discriminative ability of the extracted features. For the
21 estimation of the importance of each feature in terms of their binary classification ability, we relied on
22 the ReliefF algorithm (Robnik-Sikonja & Kononenko, 1997). The ReliefF algorithm evaluates the
23 worth of each feature by repeatedly sampling an instance and considering the value of the given feature
24 for the nearest instance of the same and different class, i.e. seizure or clear. The cumulative feature
25 ranking results across the 21+1 electrodes for all subjects and for the 20-best features are presented in
26 Table 5.

27

1 **Table 5. Cumulative feature ranking results based on ReliefF algorithm for the 20-best features.**

2

3 The ReliefF algorithm revealed the logarithmic energy entropy value, the 2nd, 3rd, 4th and 7th
4 AR-coefficients, the zero-crossing rate and the standard deviation of the signal amplitude as the most
5 discriminative features. These features were ranked within the 10-best for all three evaluated subjects.
6 Moreover, the minimum mean and maximum value of the ECG signal as well as the three ECG
7 percentiles (i.e. 25-50-75%) were evaluated within the 20-best ranked features, indicating the existence
8 of underlying information related to seizure characteristics within electrocardiographic signal. These
9 characteristics (estimated on heart rate statistics) indicate the correlation of the heart rate with epileptic
10 phenomena, which is in agreement with previous studies (Valderrama et al., 2010; Greene et al., 2007;
11 Varon et al., 2013).

12 During the online analysis of the ARMOR framework we are interested in applying tools
13 performing in real-time and with minimum computational cost. For this purpose we examined the
14 performance of the seizure detection module, in terms of precision, for different number of N-best
15 features, with respect to the ReliefF-based feature ranking algorithm. The precision for the three
16 subjects and for different number of features is illustrated in Figure 4.

17

18 **Figure 4.** Seizure detection precision (in percentages) for different number of features (N-best) for the
19 three subjects (subject 07 is denoted with squared-dots, subject 08 is denoted with circle-dots line and
20 subject 09 is denoted with triangle-dots).

21

22 As can be seen in Figure 4, for all three subjects the use of subset of features reduces the precision
23 of the seizure detector. However, the exclusion of the approximately 30% worst features still offers
24 performance comparable to the best achieved (presented in Table 4) and in combination with the
25 reduction of the computational load of the detection architecture (both in the feature extraction stage
26 and the classification stage) could be a valuable solution for the online scenario.

27 The seizure detection module, which is part of the ARMOR framework, supports both the online
28 and offline analysis of multimodal data. The configuration of the seizure detector depends on the
29 performed type of analysis. Specifically, during offline analysis there is need for as higher precision as
30 possible, and thus the computational cost of the methodology followed is not restrictive for the setup of

1 the corresponding modules of the framework. On the other hand, during the online analysis the use of
2 time-demanding and computationally costly algorithms is prohibitive, especially when wearable
3 solutions with low-powered microprocessors are used.

4 We deem the application of post-processing over the labeled epochs and/or the fusion of the
5 results with other methodologies and a priori rule-based information will further improve the overall
6 detection performance.

7
8
9

10 **5. Conclusion**

11 In this article we presented a module architecture for seizure detection. The proposed module is
12 based on short-time analysis of EEG and ECG signals using time-domain and frequency-domain
13 features. The seizure detector was evaluated on real-case clinical data of three subjects with diagnosed
14 idiopathic generalized epilepsy manifested with absences, using the support vector machine
15 classification algorithm. The achieved seizure detection accuracy was more than 90% for two of the
16 evaluated subjects and slightly lower than 90% for the third one, which is comparable with the reported
17 accuracies of other data collections. Moreover, feature ranking investigation and evaluation of the
18 seizure detector using subsets of features showed that the feature vector composed by approximately
19 800-best ranked parameters provides a good trade-off between computational demands and accuracy.

20 Although the information provided by the ECG signal cannot provide high performance scores,
21 the feature ranking evaluation showed that there are ECG extracted characteristics that could offer
22 supportive information in combination with the EEG signals, which carry most of the seizure related
23 information. This is in agreement with previous studies (Valderrama et al., 2010; Nasehi &
24 Pourghassem, 2012; Mithin et al., 2012; Valderrama et al., 2012; Leutmezer et al., 2003), which have
25 shown that the ECG signal is related to seizures.

26 The presented seizure detection module can be adapted both for an offline analysis, using a large-
27 scale combination of EEG and ECG features and for an online operation, where depending on the
28 specifications of the devices and the application, light versions can be designed by using less features
29 or less channels (electrodes), based on the per-channel feature ranking scores.

30

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6

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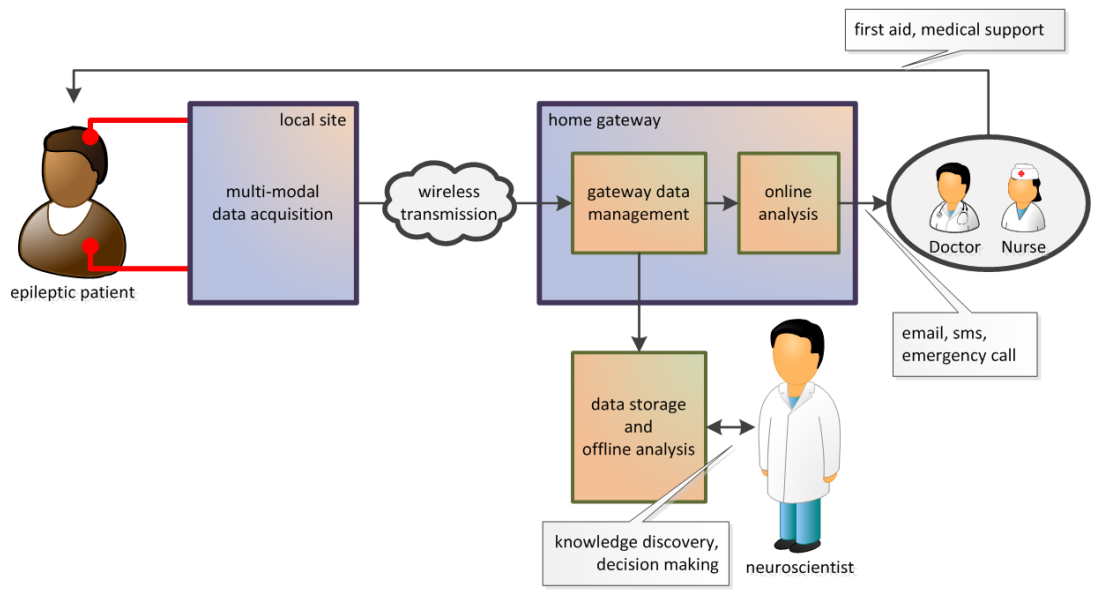
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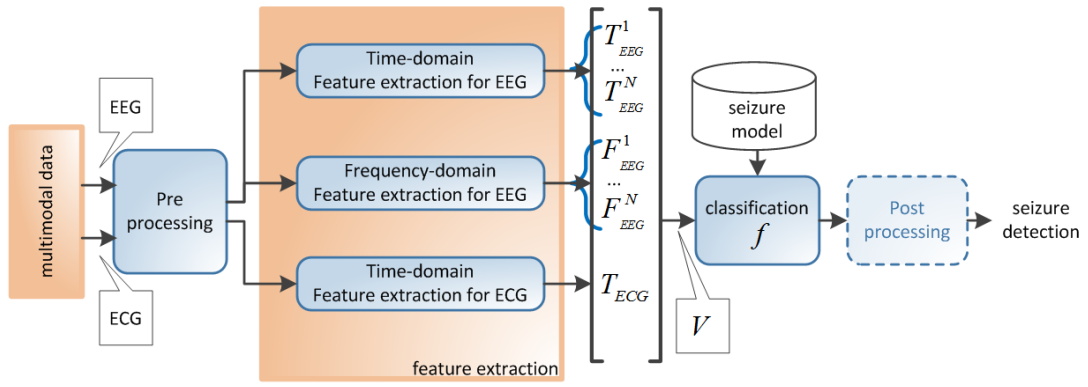
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Figure 1. The concept of the ARMOR framework.



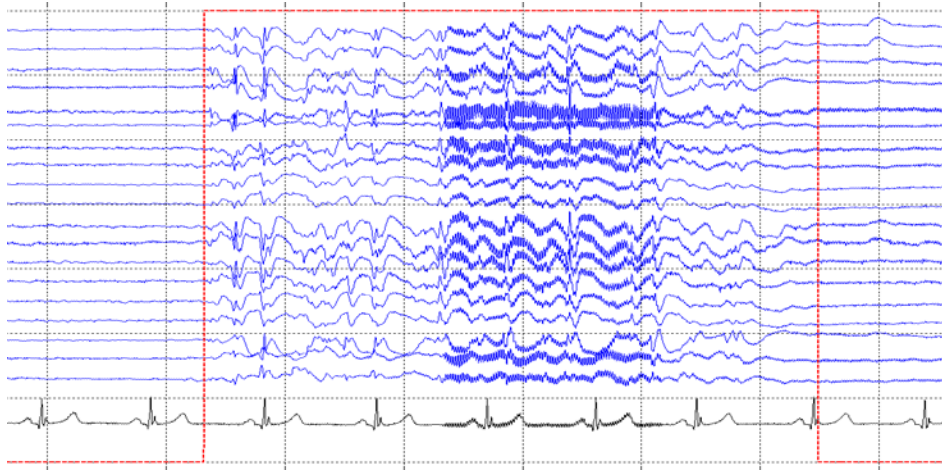
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Figure 2. Block diagram of the EEG-ECG based online seizure detection architecture.

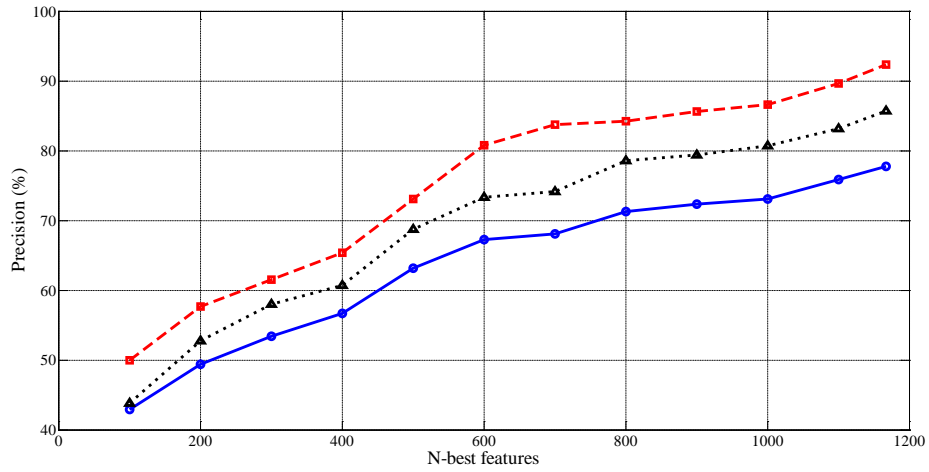
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Figure 3. Example of EEG (in blue lines) and ECG (in black line) recordings together with manual annotations (in red dotted line) of the seizure onset and offset times.



1

2 **Figure 4.** Seizure detection precision (in percentages) for different number of features (N-best) for the

3 three subjects (subject 07 is denoted with squared-dots, subject 08 is denoted with circle-dots line and

4 subject 09 is denoted with triangle-dots).

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Table 2. Seizure detection confusion matrix for subject 07

Classified as →	Seizure	Clear
Seizure	92.31	07.69
Clear	00.09	99.91

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Table 2. Seizure detection confusion matrix for subject 08

Classified as →	Seizure	Clear
Seizure	77.78	22.22
Clear	00.16	99.84

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Table 3. Seizure detection confusion matrix for subject 09

Classified as →	Seizure	Clear
Seizure	85.71	14.29
Clear	00.76	99.24

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7

1 **Table 4. Seizure detection performance for all evaluated subjects in terms of accuracy, precision**
2 **and recall.**

(%)	Sub 07	Sub 08	Sub 09
Accuracy	96.11	88.81	92.48
Precision	92.31	77.78	85.71
Recall	99.90	99.79	99.12

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1 **Table 5. Cumulative feature ranking results based on ReliefF algorithm for the 20-best features.**

no.	modality	feature	ReliefF score
01	EEG	log-energy entropy	0.29486
02	EEG	AR(2)	0.28203
03	EEG	AR(3)	0.23546
04	EEG	AR(7)	0.21728
05	EEG	AR(4)	0.18130
06	EEG	zero-crossing rate	0.15739
07	ECG	minimum value	0.13568
08	EEG	standard deviation	0.13406
09	EEG	range	0.13191
10	EEG	DWT(6)	0.13097
11	EEG	mean absolute deviation	0.12994
12	ECG	percentiles (25%)	0.12544
13	EEG	interquartiles	0.12299
14	EEG	DWT(5)	0.12292
15	ECG	mean value	0.11488
16	ECG	percentiles (50%)	0.11473
17	EEG	DWT(7)	0.10376
18	ECG	percentiles (75%)	0.09249
19	ECG	maximum value	0.08648
20	EEG	minimum value	0.08356

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