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Seizure detection using EEG and ECG signals for computer-based monitoring, analysis and management of epileptic patients

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ABSTRACT

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

1. Introduction

More than fifty million people worldwide, approximately 1% of the world population, suffer from epilepsy, which is the third most common neurological disorder in the United States after Alzheimer's disease and cerebrovascular events (Hauser, 1997). Moreover, more than 30% of the epileptic patients suffer from seizures that are refractory to medication (Kwan & Brodie, 2000). Epilepsy can directly influence patients' quality of life because of treatment-related side effects, cognitive and particularly memory dysfunction or injuries associated to seizures, potential psychiatric co-morbidities and social isolation due to stigma, especially when it runs as a long term disease (Begley et al., 2000). Moreover, there are indications that the members of the family or the caregivers of patients are also experiencing multiple psychological or social difficulties in the form of depression and social restriction (Ellis, Upton, & Thompson, 2000). Apart from these negative effects to personal and social parameters of life, the high annual budget spent for the healthcare activities related to the cost of investigation, treatment and hospitalization of epileptic patients cannot be disregarded (Ali, Elliott, & Tata, 2014; Begley et al., 2010; Hunyadi et al., 2012). The highly negative socioeconomic impact of epilepsy justifies the need for further investigation and development of technology-supported diagnostic and therapeutic systems.

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

The progress of technology over the last decades has provided the means for shifting from qualitative to quantitative clues, related to the unknown process that produces a seizure. Seizure investigation is mainly performed with quantitative analysis of the electroencephalogram (EEG) (Gotman, 1982; Nasehi & Pourghassem, 2012; Tong & Thankor, 2009; Valderrama et al., 2010). The detection of epileptic seizures is based on visual analysis of the multidimensional EEG signal (typically consisting of time-synchronous recordings captured from a 10–20 scalp electrodes system), which is performed manually by expert neurologists for the detection of patterns of interest such as spikes or spike wave complexes (Mohseni et al., 2006). This procedure is

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tedious, time-consuming (especially for long time recordings) and expensive since investigation from experts is needed. Furthermore, as there are many different patterns of clinical and electrophysiological seizure manifestation, the elaborative investigation of ictal or interictal patterns becomes demanding and complex.

Apart from the EEG, the study of electrocardiographic (ECG) signals can also offer valuable information related to the seizure discharges (Mithin, Abubeker, & Thomas, 2012; Valderrama et al., 2010). It has been shown that seizures are often associated with cardiovascular and respiratory alterations such as tachycardia (Greene, Boylan, Reilly, de Chazal, & Connolly, 2007; Nasehi & Pourghassem, 2012; Valderrama et al., 2010, 2012; Varon, Jansen, Lagae, & Van Huffel, 2013; Zijlmans, Flanagan, & Gotman, 2002). Specifically, measures related to the heart rate (e.g. mean heart rate, heart rate variability and acceleration) (Leutmezer, Schernthaner, Lurger, Potzelberger, & Baumgartner, 2003; Mithin et al., 2012; Nasehi & Pourghassem, 2012; Valderrama et al., 2010, 2012), as well as the respiration rate (Greene et al., 2007), are known to be valuable clinical signs of early manifestation of an epileptic discharge. Besides the heart-rate based characteristics, the morphology of the ECG signal is related to seizures (Varon et al., 2013). Significant changes in ECG signal characteristics indicate the need for detailed investigation of the corresponding interval of an EEG recording or may be the cause for an alert for a possible seizure.

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

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

In most of the parametric approaches found in the literature the analysis is based on the estimation of the EEG channels' spectral magnitude (Greene et al., 2007; Mohseni et al., 2006; Nasehi & Pourghassem, 2012; Valderrama et al., 2010). Other EEG features that have been reported are the autoregressive filter coefficients, the continuous and discrete wavelet transform, the energy per brain wave (delta, theta, alpha, beta, gamma) bands (Chen, 2014; Nasehi & Pourghassem, 2012; Ocak, 2009; Tong & Thankor, 2009; Valderrama et al., 2010), band-pass based features (Tang & Durand, 2012), entropy (Gandhi, Chakraborty, Roy, & Panigrahi, 2012; Kumar, Sriraam, Benakop, & Jinaga, 2010; Ocak, 2009) and phase space representation (Sharma & Pachori, 2015). In addition, time domain features have been proposed, such as zero-crossing rate (Hunyadi et al., 2012) and temporal statistics of the EEG signal amplitude per channel (Nasehi & Pourghassem, 2012; Valderrama et al., 2010). The ECG features are mainly based on the heart rate estimation (based on R–R intervals (Sabarimalai and Soman, 2012)) and its statistical measures, i.e. heart rate variability (Corsini et al., 2006; Greene et al., 2007; Nasehi & Pourghassem, 2012; Valderrama et al., 2010; Varon et al., 2013; Zijlmans et al., 2002). Features describing the morphology of the ECG waveforms by means of principal component analysis have also been used (Varon et al., 2013).

For the classification of the parameterized epochs several powerful machine learning algorithms have been reported. The most widely used are the artificial neural networks (Gandhi et al., 2012; Fatma Gulera et al., 2005; Kemal Kiymika et al., 2004; Kumar et al., 2010; Mohseni et al., 2006; Nasehi & Pourghassem, 2012; Subasi and Ercelebi, 2005) and the support vector machines (Hunyadi et al., 2012; Sharma & Pachori, 2015; Shoeb & Guttag, 2010; Shoeb et al., 2004; Tang & Durand, 2012; Valderrama et al., 2010; Zavar, Rahati, Akbarzadeh-T, & Ghasemifard, 2011). Other algorithms that have been evaluated are the k-means clustering (Varon et al., 2013), the k-nearest neighbors (Chen, 2014; Tzallas, Tsipouras, & Fotiadis, 2009; Wang, Miao, & Xie, 2011), the linear discriminant analysis (Greene et al., 2007; Liang, Wang, & Chang, 2010), the fuzzy logic (Aarabi, Fazel-Rezai, & Aghakhani, 2009; Fazle Rabbi & Fazel-Rezai, 2012), the singular value decomposition (Hassanpour, Mesbah, & Boashash, 2004), the decision trees (Polat & Gunes, 2007, 2008; Tzallas et al., 2009) and the Gaussian mixture models (Chua, Chandran, Acharya, & Lim, 2008).

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

The rest of this paper is organized as follows: In Section 2 we present the concept of the ARMOR framework and explain the purpose of seizure detection in it. Section 3 presents the proposed architecture for seizure detection from EEG and ECG signals. In Section 4 we describe the experimental setup and in Section 5 the evaluation results. Finally in Section 6 we conclude this work.

2. The ARMOR framework

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

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

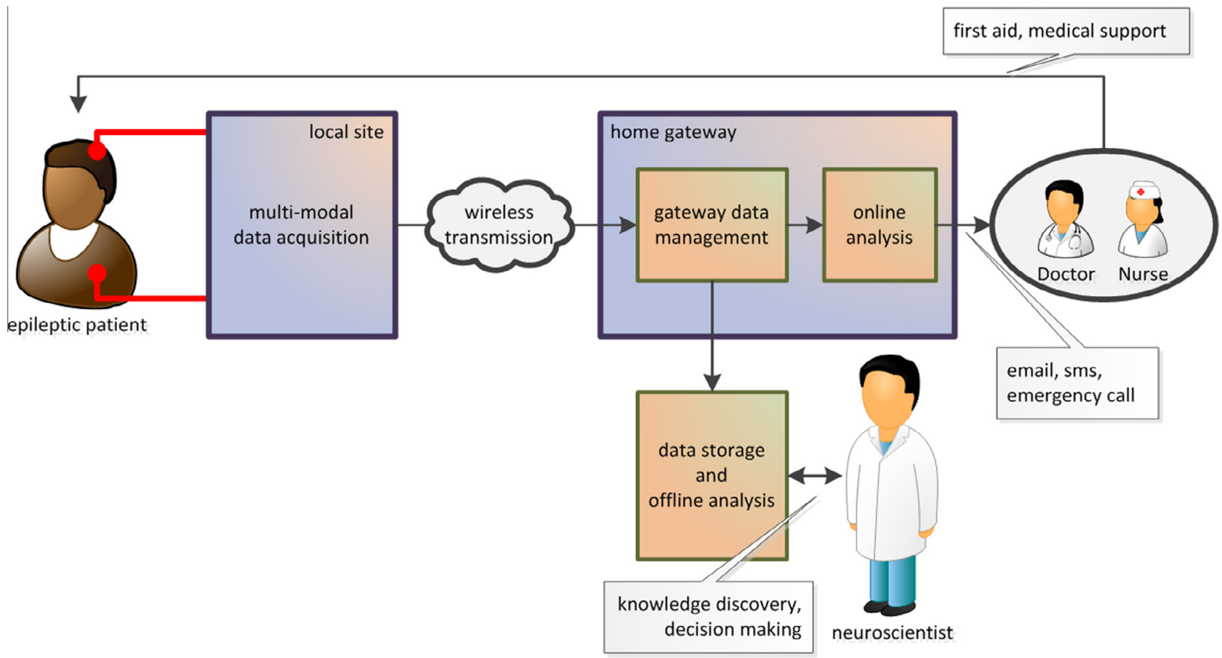

Fig. 1. The concept of the ARMOR framework.

operation is important to be investigated, while during the offline analysis the target is the maximum performance of the seizure detection algorithm.

3. Module for online seizure detection from EEG–ECG recordings

In the presented module for seizure detection only the EEG and ECG recordings are used from the multimodal recorded data. The EEG and ECG data have been proven to be very important for analysis of seizures in previous studies, while EMG and EOG have mainly been used for movement and artifact detection, and thus are not part of this study. The block diagram of the seizure detection module adopted in this study is illustrated in Fig. 2.

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

After preprocessing the extracted epochs are in parallel processed by time-domain and frequency-domain feature extraction algorithms individually for the N-dimensional EEG and the 1-dimensional ECG signals. In particular, each of the N-dimensions of the EEG signal are processed by time-domain and frequency-domain feature extraction algorithms for EEG, while the ECG signal is processed by time-domain feature extraction algorithms (based on heart rate estimation) dedicated for electrocardiogram, as shown in the block diagram of Fig. 2. The extracted time-domain and frequency-domain features for the EEG, $T^i_{\mathrm{EEG}} \in \mathbb{R}^{|T_{\mathrm{EEG}}|}$ and $F^i_{\mathrm{EEG}} \in \mathbb{R}^{|F_{\mathrm{EEG}}|}$, with $1 \leqslant i \leqslant N$, and the ECG signal, $T_{\mathrm{ECG}} \in \mathbb{R}^{|T_{\mathrm{ECG}}|}$, are afterwards concatenated to a single feature vector $V \in \mathbb{R}^{N\cdot(|T_{\mathrm{EEG}}|+|F_{\mathrm{EEG}}|)+|T_{\mathrm{ECG}}|}$ representing each epoch, as shown in Fig. 2. The extracted sequences of feature vectors, V, are short-time

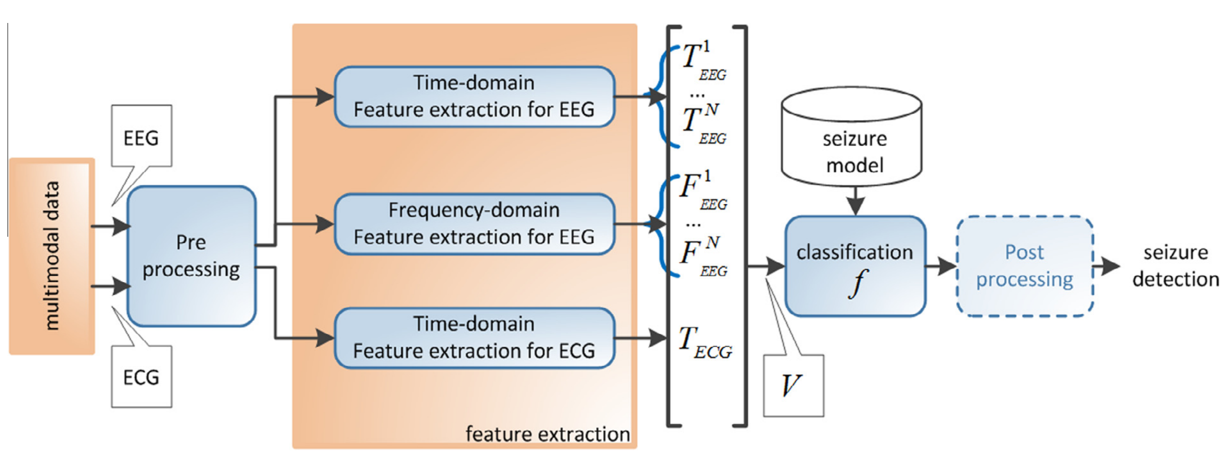

Fig. 2. Block diagram of the EEG–ECG based online seizure detection architecture.

parametric representations of the EEG and ECG signals representing the time and spectral characteristics of the multimodal signals. This sequence of feature vectors is afterwards used as input to a classification model which assigns a class label (seizure class or non-seizure class) to each of the vectors, i.e. to the corresponding time-intervals (epoch).

During pre-processing the time-synchronized EEG and ECG recordings were frame blocked to epochs of 1 s length, without time-overlap between successive epochs. For each epoch time-domain and frequency domain features were extracted separately for each of the 21 EEG channels and the ECG channel. In particular, each of the EEG channels was parameterized using the following features: (i) time-domain features: minimum value, maximum value, mean, variance, standard deviation, percentiles (25%, 50%-median and 75%), interquartile range, mean absolute deviation, range, skewness, kyrtosis, energy, Shannon's entropy, logarithmic energy entropy, number of positive and negative peaks, zero-crossing rate, and (ii) frequency-domain features: 6-th order autoregressive-filter (AR) coefficients, power spectral density, frequency with maximum and minimum amplitude, spectral entropy, delta–theta–alpha–beta–gamma band energy, discrete wavelet transform coefficients with mother wavelet function Daubechies 16 and decomposition level equal to 8, thus resulting to a feature vector of dimensionality equal to 55 for each of the 21 EEG channels, i.e. 1155 EEG features in total.

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

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

$$d_i = f(V_i, M) \tag{1}$$

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

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

4. Experimental setup

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

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

During the test phase, the EEG and ECG recordings are pre-processed and parameterized as in training. The SVM seizure detection model, M, is used to label each of the incoming EEG–ECG epochs as seizure or clear (non-seizure). In the present evaluation no post-processing algorithm was applied on the estimated epoch-based results.

5. Experimental results

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

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

As seen in the confusion matrices, the accuracy of detection of seizure varies from 92.31% (for subject 07) to 77.78% (for subject 07), while the detection of clear intervals, i.e. interval recordings without the presence of seizure, was found to be at least 99.24% for all three subjects. This variation in the accuracy of the seizure

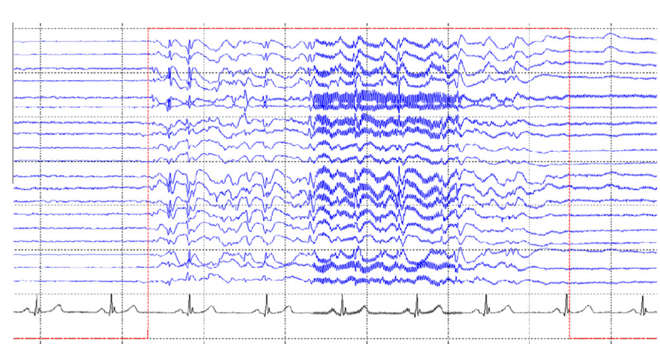

Fig. 3. Example of EEG (in blue lines) and ECG (in black line) recordings together with manual annotations (in red doted line) of the seizure onset and offset times. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Seizure detection confusion matrix for subject 07.

Classified as →	Seizure	Clear
Seizure	92.31	07.69
Clear	00.09	99.91

Table 2
Seizure detection confusion matrix for subject 08.

Classified as →	Seizure	Clear
Seizure	77.78	22.22
Clear	00.16	99.84

Table 3
Seizure detection confusion matrix for subject 09.

Classified as →	Seizure	Clear
Seizure	85.71	14.29
Clear	00.76	99.24

detection epochs (approximately 21%), compared to the more robust detection of non-seizure epochs (with variation of approximately 0.7%), is mainly owed to the limited amount of training data which does not allow the SVM algorithm to model the seizure characteristics with absolute performance. It is worth mentioning that the duration of each idiopathic generalized seizure occurrence was approximately 2 up to 4 successive epochs, while the available seizure occurrences for subject 08 were significantly fewer than the ones of subject 07, which presented the best seizure detection performance.

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

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

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

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

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

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

Table 4
Seizure detection performance for all evaluated subjects in terms of accuracy, precision 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

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

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

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

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

The seizure detection module, which is part of the ARMOR framework, supports both the online and offline analysis of multimodal data. The configuration of the seizure detector depends on the performed type of analysis. Specifically, during offline analysis there is need for as higher precision as possible, and thus the

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

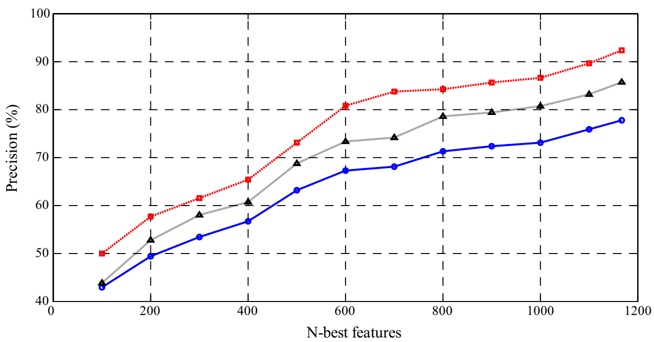

Fig. 4. Seizure detection precision (in percentages) for different number of features (*N*-best) for the three subjects (subject 07 is denoted with squared-dots, subject 08 is denoted with circle-dots line and subject 09 is denoted with triangle-dots).

computational cost of the methodology followed is not restrictive for the setup of the corresponding modules of the framework. On the other hand, during the online analysis the use of time-demanding and computationally costly algorithms is prohibitive, especially when wearable solutions with low-powered microprocessors are used.

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

6. Conclusion

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

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

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

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References

Aarabi, A., Fazel-Rezai, R., & Aghakhani, Y. (2009). A fuzzy rule-based system for epileptic seizure detection in intracranial EEG. *Clinical Neurophysiology, 120*(9), 1648–1657.

Ali, M. A., Elliott, R. A., & Tata, L. J. (2014). The direct medical costs of epilepsy in children and young people: A population-based study of health resource utilisation. *Epilepsy Research, 1211*(13).

ARMOR project. Web-site: <http://www.armor-project.eu/>.

Begley, C. E., Famulari, M., Annegers, J. F., Lairson, D. R., Reynolds, T. F., Coan, S., et al. (2000). The cost of epilepsy in the United States: An estimate from population-based clinical and survey data. *Epilepsia, 41*(3), 342–351.

Begley, C. E., Shegog, R., Iyagba, B., Chen, V., Talluri, K., Dubinsky, S., et al. (2010). Socioeconomic status and self-management in epilepsy: Comparison of diverse clinical populations in Houston, Texas. *Epilepsy & Behavior, 19*(3), 232–238.

Burges C. (1998). A tutorial on support vector machines for pattern recognition. In *Data mining and knowledge discovery* (Vol. 2, issue 2, pp. 121–167): Kluwer Academic Publishers.

Chen, G. (2014). Automatic EEG seizure detection using dual-tree complex wavelet-Fourier features. *Expert Systems with Applications, 41*, 2391–2394.

Chua, K. C., Chandran, V., Acharya, R., & Lim, C. M. (2008). Automatic identification of epilepsy by HOS and power spectrum parameters using EEG signals: A comparative study. *Conference Proceedings IEEE Engineering in Medicine and Biology Society, 2008*, 3824–3827.

Corsini, J., Shoker, L., Sanei, S., & Alarcon, G. (2006). Epileptic seizure predictability from scalp EEG incorporating constrained blind source separation. *IEEE Transactions on Biomedical Engineering, 53*(5), 790–799.

Ellis, N., Upton, D., & Thompson, P. (2000). Epilepsy and the family: A review of current literature. *Seizure, 9*(1), 22–30.

Fatma Gulera, N., Derya Ubeylib, E., & Gulera, I. (2005). Recurrent neural networks employing Lyapunov exponents for EEG signals classification. *Expert Systems with Applications, 29*(3), 506–514.

Fazle Rabbi, A., & Fazel-Rezai, R. (2012). A fuzzy logic system for seizure onset detection in intracranial EEG. *Computational Intelligence and Neuroscience, 2012*, 12.

Gandhi, T. K., Chakraborty, P., Roy, G. G., & Panigrahi, B. K. (2012). Discrete harmony search based expert model for epileptic seizure detection in electroencephalography. *Expert Systems with Applications, 39*, 4055–4062.

Gotman, J. (1982). Automatic recognition of epileptic seizures in the EEG. *Electroencephalography and Clinical Neurophysiology, 54*(5), 530–540.

Greene, B. R., Boylan, G. B., Reilly, R. B., de Chazal, P., & Connolly, S. (2007). Combination of EEG and ECG for improved automatic neonatal seizure detection. *Clinical Neurophysiology, 118*(6), 1348–1359.

Hassanpour, H., Mesbah, M., & Boashash, B. (2004). Time-frequency feature extraction of newborn EEG seizure using SVD-based techniques. *EURASIP Journal on Advances in Signal Processing, 16*, 2544–2554.

Hauser, A. (1997). Epidemiology of seizures and epilepsy in the elderly. In A. Rowan & R. Ramsay (Eds.), *Seizures and epilepsy in the elderly* (pp. 7–18). Boston: Butterworth-Heinemann.

Hunyadi, B., Signoretto, M., Van Paesschen, W., Suykens, J. A., Van Huffel, S., & De Vos, M. (2012). Incorporating structural information from the multichannel EEG improves patient-specific seizure detection. *Clinical Neurophysiology, 123*(12), 2352–2361.

Keerthi, S. S., Shevade, S. K., Bhattacharyya, C., & Murthy, K. R. K. (2001). Improvements to Platt's SMO algorithm for SVM classifier design. *Neural Computation, 13*(3), 637–649.

Kemal Kiymika, M., Akinb, M., & Subasia, A. (2004). Automatic recognition of alertness level by using wavelet transform and artificial neural network. *Journal of Neuroscience Methods, 139*(2), 231–240.

Kemp, B., & Olivan, J. (2003). European data format 'plus' (EDF+), an EDF alike standard format for the exchange of physiological data. *Clinical Neurophysiology, 114*(9), 1755–1761.

Kumar, S. P., Sriraam, N., Benakop, P. G., & Jinaga, B. C. (2010). Entropies based detection of epileptic seizures with artificial neural network classifiers. *Expert Systems with Applications, 37*, 3284–3291.

Kwan, P., & Brodie, M. J. (2000). Early identification of refractory epilepsy. *New England Journal of Medicine, 342*(5), 314–319.

Le Van Quyen, M., Soss, J., Navarro, V., Robertson, R., Chavez, M., Baulac, M., et al. (2005). Preictal state identification by synchronization changes in long-term intracranial EEG recordings. *Clinical Neurophysiology, 116*(3), 559–568.

Leutmezer, F., Schernthaner, C., Lurger, S., Potzelberger, K., & Baumgartner, C. (2003). Electrocardiographic changes at the onset of epileptic seizures. *Epilepsia, 44*(3), 348–354.

Liang, S. F., Wang, H. C., & Chang, W. L. (2010). Combination of EEG complexity and spectral analysis for epilepsy diagnosis and seizure detection. *EURASIP Journal on Advances in Signal Processing, 2010*, 853434.

Mithin, R., Abubeker, K. M., & Thomas, E. (2012). Detection of epilepsy using heart rate variability. *International Journal of Research in Antennas and Microwave Engineering – IJRAWE*, 60–65.

Mohseni, H. R., Maghsoudi, A., Shamsollahi, M. B. (2006). Seizure detection in EEG signals: A comparison of different approaches. In *Conference proceedings IEEE engineering in medicine and biology society*, 6724–7.
Nasehi, S., & Pourghassem, H. (2012). Seizure detection algorithms based on analysis of EEG and ECG signals: A survey. *Neurophysiology, 44*(2), 174–186.
Ocak, H. (2009). Automatic detection of epileptic seizures in EEG using discrete wavelet transform and approximate entropy. *Expert Systems with Applications, 36*, 2027–2036.
Polat, K., & Gunes, S. (2007). Classification of epileptiform EEG using a hybrid system based on decision tree classifier and fast Fourier transform. *Applied Mathematics and Computation, 187*(2), 1017–1026.
Polat, K., & Gunes, S. (2008). A novel data reduction method: Distance based data reduction and its application to classification of epileptiform EEG signals. *Applied Mathematics and Computation, 200*(1), 10–27.
Robnik-Sikonja, M., & Kononenko, I. (1997). An adaptation of relief for attribute estimation in regression. In *4th International conference on machine learning* (pp. 296–304).
Sabarimalai, M., & Soman, K. P. (2012). A novel method for detecting R-peaks in electrocardiogram (ECG) signal. *Biomedical Signal Processing and Control, 7*(2), 118–128.
Sharma, R., & Pachori, R. B. (2015). Classification of epileptic seizures in EEG signals based on phase space representation of intrinsic mode functions. *Expert Systems with Applications, 42*, 1106–1117.
Shoeb, A., & Guttag, J. (2010). Application of machine learning to epileptic seizure detection. In *Proceedings of the 27th international conference on machine learning*.
Shoeb, A., Edwards, H., Connolly, J., Bourgeois, B., Treves, S. T., & Guttag, J. (2004). Patient-specific seizure onset detection. *Epilepsy & Behavior, 5*(4), 483–498.
Subasi, A., & Ercelebi, E. (2005). Classification of EEG signals using neural network and logistic regression. *Computer Methods and Programs in Biomedicine, 78*(2), 87–99.
Tang, Y., & Durand, D. M. (2012). A tunable support vector machine assembly classifier for epileptic seizure detection. *Expert Systems with Applications, 39*, 3925–3938.
Tong, S., & Thankor, N. V. (2009). *Quantitative EEG analysis methods and applications*. Boston, New York, USA: Artech House.
Tzallas, A. T., Tsipouras, M. G., & Fotiadis, D. I. (2009). Epileptic seizure detection in EEGs using time-frequency analysis. *IEEE Transactions on Information Technology in Biomedicine, 13*(5), 703–710.
Valderrama, M., Alvaradoa, C., Nikolopoulos, S., Martinerie, J., Adama, C., Navarroa, V., et al. (2012). Identifying an increased risk of epileptic seizures using a multi-feature EEG–ECG classification. *Biomedical Signal Processing and Control, 7*(3), 237–244.
Valderrama, M., Nikolopoulos, S., Adam, C., Navarro, V., & Le Van Quyen, M. (2010). Patient-specific seizure prediction using a multi-feature and multi-modal EEG–ECG classification. In *XII medicine conference on medical and biological engineering and computing* (Vol. 29, pp. 77–80).
Varon, C., Jansen, K., Lagae, L., & Van Huffel, S. (2013). Detection of epileptic seizures by means of morphological changes in the ECG. *Computing in Cardiology, 40*, 863–866.
Wang, D., Miao, D., & Xie, C. (2011). Best basis-based wavelet packet entropy feature extraction and hierarchical EEG classification for epileptic detection. *Expert Systems with Applications, 8*, 14314–14320.
Witten, H. I., & Frank, E. (2005). *Data mining: Practical machine learning tools and techniques*. Morgan Kaufmann Publishing.
Zavar, M., Rahati, S., Akbarzadeh-T, M. R., & Ghasemifard, H. (2011). Evolutionary model selection in a wavelet-based support vector machine for automated seizure detection. *Expert Systems with Applications, 38*, 10751–10758.
Zijlmans, M., Flanagan, D., & Gotman, J. (2002). Heart rate changes and ECG abnormalities during epileptic seizures: Prevalence and definition of an objective clinical sign. *Epilepsia, 43*(8), 847–854.