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A new algorithm for detection of epileptic seizures based on HRV signal

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Epilepsy is one of the most frequent neurological disorders. In a significant number of cases, skilled professionals carry out the detection of the epileptic seizures manually. This necessitates automated epileptic seizure detection. Many researchers have presented computational methods for detecting epileptic seizures based on electroencephalogram signals. In this article, we propose a novel and efficient algorithm for detecting the presence of epileptic seizures in heart rate variability (HRV). This algorithm includes feature extraction and classification. Ten features include time and frequency domain analysis and nonlinear features extracted from one-lead electrocardiogram signal of epileptic patients. Extracted features were used as the input of an artificial neural network, which provides the final classification of the HRV segments (existence of epileptic seizure or not). Multilayer perceptron neural networks with different number of hidden layers and five training algorithms were designed. The results show sensitivity, specificity and accuracy of 88.66%, 90% and 88.33%, respectively, in secondary generalised and 83.33%, 86.11% and 84.72%, respectively, in complex partial seizures. The experimental results portray that the proposed algorithm efficiently detects the presence of epileptic seizure in HRV signals and showed a reasonable accuracy in detection.

Keywords: epilepsy; seizure; heart rate variability; detection; classification; multilayer perceptron

1. Introduction

Epileptic seizures result from a temporary electrical disturbance of the brain. According to the International League against epilepsy, epilepsy is recognised when a person has two or more unprovoked seizures. Sometimes seizures may remain unnoticed, depending on their exposure and sometimes disarranged with other events, such as a stroke, which can also cause falls, faints or migraines (Iasemidis et al., 2003). Epilepsy is the second most common neurological disorder, next to stroke, affecting 50 million people worldwide. Of these individuals, 25% do not respond to existing medications (Epilepsy Foundation of America, 1999). Epileptic seizures are classified as ‘partial’ when the electrical discharge causing it occurs in a specific or particular area of the brain, or ‘generalised’ when the discharge reliefs the entire brain cortex (Aragon & Burneo, 2007).

Complex partial (CP) epileptic seizures confine to a particular region, but have spread enough that patients have an impaired level awareness about their surroundings. This seizure is
common, particularly involving the temporal lobe. Patients with CP seizures may exhibit symptoms such as glassy stares and lack of response, inappropriate or confused responses to questions, sitting, standing, walking aimlessly, lip smacking or chewing motions, unusual vocal sounds and fidgeting (Archer, Abbott, Waites, & Jackson, 2003; Gotman et al., 2005; Laufs, Lengler, Hamandi, Kleinschmidt, & Krakow, 2006).

Partial seizures with secondary generalisation (SG) are focal seizures that spread to both sides of the brain causing a grand mal convulsion. They begin as simple or CP seizures, but then spread (generalise) to the rest of the brain and look like generalised tonic–clonic seizures (Forsgren, Bucht, Eriksson, & Bergmark, 1996; Jobst et al., 2001; Schindler, Leung, Lehnertz, & Elger, 2007; Theodore et al., 1994). These two types can easily be confused, but they are treated differently. Except for beginning locally and spreading, partial seizures look the same as the generalised tonic–clonic seizure. CP seizure is described as the patient’s ‘small seizure’ and the SG as ‘big seizures’.

The mortality rate in epilepsy is two to three times that of the general population (Hitiris, Mohanraj, Norrie, & Brodie, 2007), and sudden unexplained death in epilepsy patients (SUDEP) appears to be the most common cause of epilepsy-related death (Tomson, Nashef, & Ryvlin, 2008). SUDEP is defined as the sudden unexpected death of a person with epilepsy without reasonable anatomic or toxicological explanation (Ficker, 2000). The cause of SUDEP is unknown, although a number of mechanisms suggested, including cardiac arrhythmia precipitated by seizure discharge acting via the autonomic nervous system (ANS), respiratory arrest and neurogenic pulmonary oedema (Surges, Scott, & Walker, 2009).

Epileptic seizures are often accompanied by changes in various autonomic functions such as heart rate (HR) and affect ANS in a complex way. Changes in HR can occur prior, during or after clinical manifestations of the seizure. Autonomic changes may lead to sudden death in epileptic patients. These changes are not fully understood, but may be the result of increased motor activity, emotional distress or modulation of central autonomic circuitry (Ansakorpi et al., 2002; Epstein, Sperling, & O’Connor, 1992; Freeman & Schachter, 1995).

Heart rate variability (HRV) analysis used to investigate a variety of clinical situations including diabetic neuropathy, myocardial infarction, congestive heart failure and sudden death (Sztajzel, 2004). Abnormal nonlinear HRV may predict sudden cardiac death (Stein, 2006). The association between seizures and HR changes has been documented since 30 years ago in studies in patients with partial seizures (Blumhardt, Smith, & Owen, 1986; Marshall, Westmoreland, & Sharbrough, 1983). Several studies have demonstrated that HR usually increases during the seizures (Ansakorpi et al., 2002; Epstein et al., 1992; Freeman & Schachter, 1995; Luders & Noachtar, 2000; Nashef et al., 1996; Opherk, Coromilas, & Hirsch, 2002), but bradycardia (Britton, Ghearing, Benarroch, & Cascino, 2006) and even cardiac asystole (Carvalho, Salanova, & Markand, 2004) can occasionally occur during temporal lobe seizures.

Partial and generalised epilepsies alter autonomic function during ictal, postictal and interictal states. All aspects of autonomic function are affected, including the parasympathetic, sympathetic and adrenal medullary systems.

Sinus tachycardia can occur in more than 85% of CP and tonic–clonic seizures (Opherk et al., 2002). Among partial seizures that do not generalise, ictal tachycardia may be more prominent after mesial temporal than after non-lesional or extra temporal seizures. Ictal tachycardia may be significantly higher than abnormalities of rhythm or repolarisation, more frequent during, or immediately after, generalised than non-generalised seizures (Nei, Ho, & Sperling, 2000; Opherk et al., 2002).

Until now, several methods developed to detect the pre-ictal transition and epileptic seizures (Najumnissa & Rangaswamy, 2012; Ocak, 2009; Quyen et al., 2001; Srinivasan,
Eswaran, & Sriraam, 2007; Subasi, 2005). Most of these methods work backward in time and try to identify the changes of the estimated measures from the electroencephalogram (EEG) near the seizure, as compared with the ones from a reference EEG segment typically arbitrarily selected far from the seizure. The classifying methods based on information extracted from EEG signals of epileptic patients, which have been proposed during the last decade include digital signal analysis, Fuzzy Logic methods, Artificial Neural Network (ANN), Hidden Markov Model, Genetic Algorithm, Support Vector Machines, Self-Organising Map, Bayesian and other methods, with each of them exhibiting its own advantages and disadvantages.

As epileptic patients show symptoms of ANS dysfunction, HRV fluctuation before, during and after epileptic seizures, and as the analysis of HRV is a powerful and non-invasive tool for assessing the ANS activities and cardiovascular autonomic regulation (Sztajzel, 2004), in this study we propose an efficient algorithm for detecting the presence of epileptic seizures in HRV signals. The main goal of this study is to detect and classify the epileptic seizures through the processing of extracting HRV features.

Feature extraction is applied based on evaluating the effect of motor activity on the HR changes in the ictal phase of epileptic seizures. As time and frequency domain analyses of HRV are less successful in the classification of HR changes, we will extract nonlinear dynamics of HRV in order to quantify complex structures in HR time series. Therefore, several features include time and frequency domain analysis and nonlinear features extracted from one-lead electrocardiogram (ECG) signal of epileptic patients in order to classify non-epileptic and epileptic HRV signals. These features are used as inputs of an ANN, which classifies each segment into one of the mentioned classes.

We propose different structures of neural networks, capable of classifying the non-epileptic and epileptic segments, using as evaluation metrics: accuracy, sensitivity and specificity. We attempt to identify winning characteristics that could get an accurate classification in used dataset, by training the neural networks and test them in different ways.

The paper is organised as follows. Section 2 describes the database and features extraction methods. Section 3 presents the neural networks studied including a brief description of training, validation and test of neural work. In Section 4, the performance measure methods and experimental results are described, and in Sections 5 and 6, the discussion and conclusions are presented, respectively.

2. Materials and methods

2.1 Data description

One-lead ECG recordings of patients with pharmaco-resistant focal epilepsies compiled as part of the EPILEPSIAE project (Ihle et al., 2012). Recordings were obtained at the epilepsy units of the University Hospital of Freiburg, Germany, the Pitié-Salpêtrière Hospital of Paris, France and the University Hospital of Coimbra, Portugal, which contribute EEG and ECG data from long-term monitoring of epileptic patients, as well as standardised annotations. The sampling rates of the data were 256, 512 and 1024 Hz, and filtered for line noise at 50 Hz. Clinical features of epileptic patients are listed in Table 1. The total number of 206 seizures was collected from 15 patients [8 males and 7 females; mean age of 42.2 years, standard deviation (SD): 12.64 years] comprising 96 SG seizures (six patients) and 110 CP seizures (nine patients). In all cases, the EEG was recorded to confirm the seizure onset.

Two main criteria were considered for choosing the patients. Patients were chosen with seizure intervals more than 5 h to have secure borders to select the free seizure segments far
From the seizures, and avoid the effects of seizures on HRV. The second criterion applied based on the assessment of HRV during the day and night. As the HR variables have different values during the day and night, the patients who have seizures during the day were selected. HRV segments were selected only from the day parts of ECG recordings.

2.2 Feature extraction

The methods for HRV analysis are divided into linear (time and frequency domain) and nonlinear. In this work, we explore a combination of linear and nonlinear features. HRV signals are analysed using EPILAB; a MATLAB® toolbox, for the epileptic seizure prediction that allows studying epileptic seizures based on a high dimensional feature space (Teixeira et al., 2011). The extracted features are listed in Table 2. The mean HRs, maximum beat per minute (MBPM) and mean RR interval were measured at the time domain analysis of HRV.

In the frequency domain analysis, spectral measures were obtained by the Fast-Fourier Transform method. The power in the HR spectrum is divided into two components: low

Table 1. Clinical features of 15 studied patients.

<table>
<thead>
<tr>
<th>ID</th>
<th>Sex</th>
<th>Age</th>
<th>Seizure type</th>
<th>Localisation</th>
<th>Number of seizure</th>
<th>Recording time (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>M</td>
<td>47</td>
<td>CP, UC</td>
<td>T</td>
<td>6</td>
<td>93.68</td>
</tr>
<tr>
<td>2</td>
<td>F</td>
<td>37</td>
<td>CP, SP, UC</td>
<td>T</td>
<td>11</td>
<td>243.72</td>
</tr>
<tr>
<td>3</td>
<td>F</td>
<td>62</td>
<td>CP</td>
<td>T</td>
<td>6</td>
<td>164.43</td>
</tr>
<tr>
<td>4</td>
<td>F</td>
<td>35</td>
<td>CP</td>
<td>P</td>
<td>9</td>
<td>158.41</td>
</tr>
<tr>
<td>5</td>
<td>M</td>
<td>31</td>
<td>CP, SP, UC</td>
<td>F</td>
<td>15</td>
<td>163.98</td>
</tr>
<tr>
<td>6</td>
<td>F</td>
<td>54</td>
<td>CP, UC</td>
<td>T</td>
<td>10</td>
<td>94.38</td>
</tr>
<tr>
<td>7</td>
<td>M</td>
<td>58</td>
<td>CP</td>
<td>T</td>
<td>9</td>
<td>160.39</td>
</tr>
<tr>
<td>8</td>
<td>M</td>
<td>48</td>
<td>CP, SP</td>
<td>T</td>
<td>14</td>
<td>237.63</td>
</tr>
<tr>
<td>9</td>
<td>M</td>
<td>39</td>
<td>CP, SP, UC</td>
<td>T</td>
<td>30</td>
<td>113.83</td>
</tr>
<tr>
<td>10</td>
<td>M</td>
<td>46</td>
<td>SG, UC</td>
<td>F</td>
<td>7</td>
<td>68.97</td>
</tr>
<tr>
<td>11</td>
<td>M</td>
<td>51</td>
<td>SG, SP</td>
<td>T</td>
<td>6</td>
<td>118.5</td>
</tr>
<tr>
<td>12</td>
<td>F</td>
<td>34</td>
<td>SG, SP</td>
<td>F</td>
<td>11</td>
<td>133.79</td>
</tr>
<tr>
<td>13</td>
<td>F</td>
<td>50</td>
<td>SG, UC</td>
<td>T</td>
<td>14</td>
<td>163.04</td>
</tr>
<tr>
<td>14</td>
<td>M</td>
<td>17</td>
<td>SG, SP</td>
<td>T</td>
<td>31</td>
<td>143.34</td>
</tr>
<tr>
<td>15</td>
<td>F</td>
<td>24</td>
<td>SG, SP, UC</td>
<td>F</td>
<td>27</td>
<td>186.64</td>
</tr>
<tr>
<td>Total</td>
<td>206</td>
<td></td>
<td></td>
<td></td>
<td>2244.73</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Sz, type of the clinical seizures; SG, secondarily generalized; SP, simple partial; CP, complex partial; UC, UN-classified; T, temporal; P, parietal; F, frontal; Avg. dur. (min), average seizure duration for each patient in minute.

Table 2. Feature schemes.

<table>
<thead>
<tr>
<th>ID</th>
<th>Feature</th>
<th>Number of features</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Mean HRV, MBPM, RR intervals</td>
<td>3</td>
<td>Linear-time domain analysis</td>
</tr>
<tr>
<td>2</td>
<td>LF, HF, LF/HF</td>
<td>3</td>
<td>Linear-frequency domain analysis</td>
</tr>
<tr>
<td>3</td>
<td>SD1, SD2, SD1/SD2, S</td>
<td>4</td>
<td>Non-linear-Poincare plot</td>
</tr>
</tbody>
</table>

Notes: MBPM, maximum beat per minute; RR intervals, mean of all RR intervals in each segment; LF, low frequency; HF, high frequency; LF/HF, low frequency to high frequency ratio; SD1, standard deviation of instantaneous beat-to-beat RR interval variability; SD2: standard deviation of continuous long-term RR interval variability; SD1/SD2, short-term variability to long-term variability ratio; S, area of the ellipse fitted to the Poincaré plot.
frequency (LF, 0.04–0.15 Hz) and high frequency (HF, 0.15–0.4 Hz). It is well-known that HF is a marker of sole parasympathetic activity, and LF is mainly a measure of sympathetic activity with some influence from the parasympathetic nervous system (Demaree & Everhart, 2004; Fallo, Maffei, & Dalla Pozza, 2009; Halliwill, Taylor, & Eckberg, 1996; Yang, Chao, Kuo, Yin, & Chen, 2000). In other words, the HF fluctuation of the RR interval mainly reflects the cardiovagal modulation and the inspiratory inhibition of the vagal tone, whereas the LF band is thought to reflect sympathetic excitation (Pagani et al., 1997), sympathovagal balance (Eckberg, 1997) and arterial pressure oscillations (Madwed, Albrecht, Mark, & Cohen, 1989).

To differentiate the influence of the parasympathetic activity on the LF spectral power, the LF/HF ratio (which is an indicator of sympathovagal balance) was calculated (Stein, Bosner, Kleiger, & Conger, 1994). High values of this ratio indicated dominant sympathetic activity.

Considering the complex system of cardiovascular as a nonlinear system, the system dynamics is better understood. A relatively recent tool for HRV analysis is the Poincaré plot, which does not require the HRV signal to be stationary (Carvalho, da Rocha, de Oliveira Nascimento, Neto, & Junqueira, 2002). Poincaré plot, which is a graphical representation of the correlation between successive RR intervals, the SD of instantaneous beat-to-beat RR interval variability (SD1) and continuous long-term RR interval variability (SD2) were assessed using quantitative two dimensional vector analyses (Tulppo, Makikallio, Takala, Seppänen, & Huikuri, 1996; Korpelainen, Sotaniemi, Makikallio, Huikuri, & Myllylä, 1999). SD1 describes the magnitude of the beat-to-beat variability reflecting vagal modulation of the HRV and has a relatively strong correlation with the HF spectral component. SD2 describes the long-term RR interval fluctuation and reflects the magnitude of the LF spectral component. One advantage of the Poincaré method over spectral analysis techniques is that it is not sensitive to stationary irregularities and trends in RR intervals. Therefore, it became more suitable for HRV analysis (Tulppo et al., 1996).

In addition, we use the combination of Poincaré parameters to form two additional descriptors. The descriptors are $S = \pi \cdot \text{SD1} \cdot \text{SD2}$ and SD1/SD2 ratio.

The $S$ value corresponds to the area of the ellipse fitted to the Poincaré plot, and the SD1/SD2 ratio is defined by analogy as the LF/HF ratio from the spectral HRV analysis. There are some reasons to indicate that $S$ illustrates the total HRV, and SD1/SD2 ratio describes the sympathovagal balance. $S$ and SD1/SD2 ratio, by analogy with the LF/HF ratio, help to derive additional information from SD1 and SD2 that is not available if these two descriptors are considered separately (Guzik et al., 2005).

The highest correlation for $S$ is found with baroreflex sensitivity, suggesting that the area of Poincaré plot represents the total variability of HRV and is under strong vagal influence (Eckberg, 1997; Parati, Saul, & Castiglioni, 2004; Tulppo, Mäkikallio, Takala, Seppänen, & Huikuri, 1998).

3. Classification using ANNs

Classification is one of the most frequently encountered decision-making tasks of human activity (Zhang, 2000), and neural networks have emerged as a significant classification tool. Their statistical nonlinear character gives them clear precedence over traditional classifiers in many applications (Hu, Tompkins, Urusti, & Afonso, 1994; Zhang, 2000). The decision-making process of the ANN is holistic, based on the features of input patterns, and is suitable for classification of biomedical data.

The multi-layer perceptron (MLP) neural networks belongs to the class of supervised learning networks, in which the discriminating power is gained through a preliminary learning
phase, where labelled examples are presented to the network. It works by computing the error between the returned and known desired output, employing it to adjust the MLP weights. Typically, multilayer feed forward neural networks were trained as nonlinear classifiers using the generalised back propagation algorithm (BPA). The BPA is a supervised learning algorithm, in which a sum square error function is defined, and the learning process aims to reduce the overall system error to a minimum.

Although the training process in MLP requires a rather long time, the implementation and execution of a trained MLP are very simple, making it suitable for classification for ambulatory settings (Mar, Zaunseder, Martínez, Llamedo, & Poll, 2011). Therefore, in this study, the MLP is applied to classify HRV signals. The architecture of the MLP back propagation neural network is shown in Figure 1.

Training a neural network is viewed as the minimisation of an error function. The performance is improved if suitable error functions and minimisation algorithms are chosen. Regarding the minimisation algorithm, we selected five different back propagation-training algorithms. These algorithms vary in their convergence speed, memory requirement and total time to train. To facilitate the performance comparison of different training algorithms, we used their acronyms. Table 3 shows the training algorithms and their acronyms. The block diagram of proposed algorithm is presented in Figure 2.

### 3.1 Training, validation and test of neural network

The data consist of two sets each containing HRV segments with 5-min duration. These segments cut out from continuous ECG recording. Non-epileptic set contained seizure-free intervals randomly selected from the segments far from the seizure and the epileptic set contained seizure activity. As the durations of seizures are different and have less than 5-min duration, a part of pre-ictal of each seizure is considered into epileptic segments to have the segments with equal duration to non-epileptic segments.

Previous research showed different behaviours in epileptic seizures and the symptoms of tachycardia, bradycardia, fluctuation and the arrhythmia might be occurring in different types of seizures (Goldberger, 1999; Mohanraj et al., 2006; Nobili et al., 2010; Schanabel, Beblo, May, & Burmester, 2002; Stöllberger & Finsterer, 2004; Surges, Scott, & Walker, 2010; Tinuper et al., 2001; Walczak et al., 2001; Wilder-Smith & Lim, 2001). Therefore, to better evaluate the classifiers, the classifications were performed separately for each type of the seizures (SG and CP seizures). The seizures were divided into two groups; the CP seizures (include nine patients with 110 seizures) and the SG seizures (include six patients with 96 seizures).

---

**Figure 1.** Architecture of MLP neural network.
A total number of 10 features, extracted from linear and nonlinear analyses, were used to train the MLP neural network. Various network architectures were evaluated to find an optimum solution for classification of HRV into the correct groups (epileptic seizure and non-epileptic segments).

To evaluate the system performance, the number of hidden layers, as well as the number of neurons in the hidden layers, varied in different experiments. The output (target) vector is defined by a combination of 1 or 0 s to represent each of the classes being recognised. To assign the HRV signals into one of two classes, the number of neurons in the output layer is set to be two.

We investigated two architectures of MLP neural networks. NET1 has a single hidden layer with three neurons and NET2 has two hidden layers with two neurons in each layer. Other parameters of architectures were the same. Both layers use a hyperbolic tangent sigmoidal squashing function.

To train the networks, the data are divided into three sets: (1) training, (2) validation and (3) test. The training set contained the data that are used to update the synaptic weights. The performance of the networks was evaluated on the validation set after each iteration and the training stopped if the minimal gradient was reached. The test sets were used to measure the performance of the network after the training. Precisely, 70% of the input vectors of each class (CP and SG seizures) were used to train the network and 15% to validate how well the network generalises. Finally, the last 15% of the signal vectors provided a clear test set of the network generalisation using data that the network has never encountered before.

4. Experimental results

In this section, we present the performance measure methods used to evaluate the proposed algorithm. Finally, we give the experimental results and discuss our observations.
4.1 Performance measure

To evaluate the performance of the proposed classifier, three measures are used and defined as follows:

\[
\text{Sensitivity (\%)} = \frac{TP}{TP + FN} \times 100, \tag{1}
\]

\[
\text{Specificity (\%)} = \frac{TN}{TN + FP} \times 100, \tag{2}
\]

\[
\text{Accuracy (\%)} = \frac{TP + TN}{TP + FN + TN + FP} \times 100, \tag{3}
\]

where TP, TN, FP and FN stand for true positive, true negative, false positive and false negative, respectively.

If, for example, a segment of HRV with the epileptic seizure is classified as the epileptic seizure, then it is said that the segment is classified as TP. On the other hand, if a non-epileptic segment classified as non-epileptic, then it is said that the segment is classified as TN. Any non-epileptic segment, which is classified as an epileptic segment by mistake, will produce an FP, while any epileptic segment, which is classified as a non-epileptic segment by mistake, will produce a FN result.

4.2 Mean squared error

The mean squared error (MSE) is computed by taking the differences between the target and the actual neural network output, squaring them and averaging over all classes and internal validation samples. As the neural network’s outputs are real numbers between 0 and 1, this result in a MSE between 0 and 1. The neural network trained iteratively; therefore, the MSE should drop to some small and stable values. We set the maximum number of epochs as 1000 and the performance goal (MSE) as $10^{-5}$.

4.3 Classification results

Fifteen patients with mean age 42.2 years and SD 12.64 years which include 206 seizures (96 SG and 110 CP seizures) were included in this study. All the experiments of this section were done over 5-min HRV segments for each class of seizure and non-seizure mentioned in Section 2.1. There were two diagnosis classes: non-seizure and seizure that is subject to epileptic seizure. Table 4 shows the results of classification of test data for each class.

The best MSE validations were 0.0037 and 0.0258 for NET2 (two hidden layers MLP with two neurons in each layer), achieved at epoch 35 and 56 for SG and CP seizures, respectively (Figure 3).

The comparative evaluations were done for all the algorithms with both structures of MLP, which are tabulated in Table 4. Training the neural network with LM algorithm is faster than other algorithms.

With the LM algorithm, the number of iterations taken to achieve the performance goal is less than others; 35 iterations with NET2 for CP and 56 iterations for SG seizures when compared to the performance with NET1 (39 iterations for CP and 65 iterations for SG). Therefore, the Levenberg–Marquardt (LM) training algorithm gives the best accuracy (88.33% and 84.72% for SG and CP seizures, respectively) in both seizure groups.
With other algorithms, the neural network takes more epochs to reach the defined MSE, which is zero. The RP achieved 79.16% and 81.66% accuracy for CP and SG seizures, respectively, but it takes 40 and 66 number of iterations to reach the performance goal. CGP, CGB and OSS algorithms provide 76.66%, 76.66% and 74.99% classification accuracies for SGs and 75%, 77.77% and 77.77% for CP seizures, respectively. However, they take more iteration to achieve the performance goal of zero MSE, compared to the LM and RP training algorithm. Therefore, it is easier to classify the HRV signals of epileptic seizures using the LM algorithm.

The performance analysis of two MLP structures with lower MSE (LM and RP) and less iteration to reach the performance goal in terms of sensitivity, specificity and accuracy is summarised in Table 5. The best result is achieved for SG seizures with 86.66% and 90% and for CP seizures with 83.33% and 84.72%, for sensitivity and specificity, respectively.

![Figure 3](https://example.com/figure3.png)

Figure 3. The best MSE during training, validation and test obtained with the LM training algorithm: (A) NET2 (2*2), SG and (B) NET2 (2*2), CP.

<table>
<thead>
<tr>
<th>Network hidden layers</th>
<th>Epoch at which performance goal is met</th>
<th>Total number of iterations</th>
<th>Lowest MSE obtained</th>
<th>Overall accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>One hidden layer</td>
<td>Training function</td>
<td>NET1 (CP)</td>
<td>NET1 (SG)</td>
<td>NET2 (CP)</td>
</tr>
<tr>
<td>NET1 (3)</td>
<td>RP</td>
<td>62</td>
<td>45</td>
<td>74</td>
</tr>
<tr>
<td>NET1 (3)</td>
<td>CGB</td>
<td>67</td>
<td>47</td>
<td>78</td>
</tr>
<tr>
<td>NET1 (3)</td>
<td>CGP</td>
<td>79</td>
<td>62</td>
<td>99</td>
</tr>
<tr>
<td>NET1 (3)</td>
<td>OSS</td>
<td>69</td>
<td>56</td>
<td>66</td>
</tr>
<tr>
<td>NET1 (3)</td>
<td>LM</td>
<td>65</td>
<td>39</td>
<td>68</td>
</tr>
<tr>
<td>Two hidden layer</td>
<td>Training function</td>
<td>NET2 (CP)</td>
<td>NET2 (SG)</td>
<td>NET2 (CP)</td>
</tr>
<tr>
<td>NET2 (2*2)</td>
<td>RP</td>
<td>66</td>
<td>40</td>
<td>73</td>
</tr>
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Diagnosing epilepsy is a difficult task requiring observation of the patient, recording bio-signals such as EEG, ECG and MRI images and gathering additional clinical information. Therefore, a trustworthy tool such as ANN that classifies subjects as having or not having an epileptic seizure provides a valuable diagnostic decision support tool for neurologists treating epileptic patients, since differing etiologies of seizures result in different treatments.

HRV analysis is a valid method for quantifying central influences on autonomic cardiac changes, and can give valuable information when used as an adjunct during clinical seizures. Different mechanisms are implicated in the generation of ictal HR changes in epileptic patients. Increased adrenergic activities during seizures have been observed in animals (Wilder-Smith & Lim, 2001) and may account for ictal tachy-arrhythmias being much more common than brady-arrhythmias. Studies on the incidence of ictal HR changes report tachycardia in over 90% of partial seizures depending on the criteria used for tachycardia (Wilder-Smith & Wilder-Smith, 1995). Methodological differences in definition and quantification of tachycardia may play a role.

Based on previous studies (Ansakorpi et al., 2002; Harnod et al., 2009; Metcalf, Radwanski, & Bealer, 2009; Mukherjee et al., 2009; Persson, Ericson, & Tomson, 2007), indicators of HRV could be used to predict SUDEP risk and guide epilepsy treatment. It has been hypothesised that SUDEP is primarily due to increased sympathetic regulation (Hallioglu et al., 2008; Metcalf et al., 2009). Therefore, treatments that reduce sympathetic activity are favoured to reduce the risk of sudden death (Persson, Ericson, & Tomson, 2003).

During a seizure, the ANS responds by decreasing the vagal tone and increasing the HR to meet the physical demands of the seizure. Instead, in some of generalised seizures, there is an inappropriate initial increase in vagal tone which leads to an initial decrease in HR. This mismatch between the vagal tone and the seizure demand could lead to cardiac arrhythmia and SUDEP in some individuals with low HRV.

As the knowledge about the pathophysiological background of SUDEP increases, it is essential to continue to develop and create new methods to study ANS function in patients with epilepsy along with identifying the clinical risk factors.

The main objective of this study was to extract relevant features from one-lead ECG signals of epileptic patients to classify them into non-epileptic and epileptic HRV signals. As previous research showed different behaviours of epileptic seizures, the classification is performed separately for each type of seizures. The classification of cardiac dysfunctions, arrhythmias and other disorders by the neural network classifier requires generation of input vectors, which should include distinguishing features capable of properly representing the rhythm, morphology of the arrhythmia or cardiac disorders. Therefore, 10 features were extracted from HRV signals based on the time and frequency domain analysis and nonlinear method.

MLP classifier was used to classify two classes of HRV signals. Evaluation of the system performance, the number of hidden layers, as well as the number of neurons in the hidden layers and training algorithm variables, varies in different experiments.
The results showed better performance of NET2, which was MLP with two hidden layers and two neurons in each layer. In terms of learning algorithms, it is difficult to determine, which of the training algorithms are faster for the given task, since it depends on many factors such as the complexity of the problem, the number of data points in the training set, the number of weights and biases in the network, error goal and the application being used. As shown in Table 4, most of the algorithms have a good convergence, but the LM algorithm shows the highest speed of convergence. To compare training algorithms for classification of HRV signals, accuracy, sensitivity and specificity are calculated for each class. It can be seen that the LM algorithm achieved the best performance for all MLP neural networks considered in this study.

Selected features were suitable for detection, classification of epileptic and non-epileptic segments and enhanced efficiency, simplicity and recognition rate of the classification process. The HRV signal classification using the proposed algorithm was satisfactory.

The results suggest that this method may be a useful tool to detect the alterations of autonomic cardiac functions. It is evident that the combination of linear and nonlinear features together with the employed classifier is very effective. The main advantage of this method is that it applied based on RR-interval signal, which can be extracted with high accuracy even in noisy or complicated ECG recordings, while the extraction of other ECG features or any other type of ECG analysis is seriously affected by noise. We can conclude that the HRV signal can be used as a reliable indicator of different kinds of heart disorders especially in epileptic seizures.

6. Conclusion

Detection of epileptic seizures is mostly done by a small number of skilled professionals. Automating this process presents many advantages and among them are faster diagnosis, non-stop monitoring and reduction in the overall cost of medical treatment. Epileptic seizure detection using HRV analysis seems to be a reliable method for non-invasive seizure detection in the early phase of the clinical event. In the present study, an algorithm for detection and classification of epileptic seizures and non-epileptic segments employing ANN techniques was developed and implemented. The proposed algorithm consists of two phases: the feature extraction and the classification phase.

The decision-making process is performed using features extracted from HRV signals. Emphasis is placed on the selection of the characteristic features and accurate extraction of them. From the results, it can be seen that the LM BPA provided an excellent performance. The performance and trade-off between the five training methods are also studied.

It is well-known that the choice of the best algorithm is a trade-off between the performance, convergence power and training input. The proposed LM approach exhibited a superior performance in terms of classification accuracy.

The efficiency of the ANN would be more reliable if more training data are collected to train the neural network and the results would be safer. The above procedure is a successful classification method for classification of epileptic and non-epileptic segments of HRV using an MLP neural network; therefore, it can be applied to more complex medical conditions, acting as an additional tool of diagnosis by the physician. Of course, the proposed methodology would not be used in order to replace the physician, but only by means of an additional evaluation method.

Although the classifiers show good results, there is an evident degradation of performance in different types of epileptic seizures. This is probably because the patients have different types of epilepsy and the networks may not have sufficient generalisation capability. This seems to indicate that seizure detection, prediction and classification with neural networks need a personalised network that is specific for each patient.
The results show that it is possible to find a good classifier based on HRV information on epileptic patients (with the accuracies of 88.33% and 84.72%, for SG and CP seizures, respectively). However, HR signals vary significantly depending on many factors such as individual differences and time. Therefore, the classifier of one patient cannot be used for another patient. The variability of physiological systems can only be overcome by personalising the architecture and the training of the network. If the classifier design is to give the patient an alarm of an approaching seizure (classifying correctly the pre-ictal state), it should be checked by both sensitivity and specificity. If one limits to only one of them, no practical usefulness can be given to the results.

Results suggest that combination of selected linear and nonlinear features together with employed classifier is very effective in classification of HRV signals into epileptic and non-epileptic groups. However, further study needs to conclude which nonlinear features should be used together with the standard linear time and frequency domain features in HRV analysis to obtain better results.

In addition to the selection of the best feature sets for classification, classifier type and architecture might have a vital role in classification results. Although the LM algorithm converges faster than others (Hagan & Menhaj, 1994), it is memory-intensive. Therefore, further examination of other classifiers (supervised or unsupervised) with higher overall recognition accuracies would be studied in our future works.

In addition, it would be interesting to study HR inter-ictal and ictal variables to evaluate whether inter-ictal changes correlate with ictal changes in the same patient. This finding can lead us to find an algorithm for prediction of epileptic seizures based on HRV signals.

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