Combined Matching Pursuit and Wigner-Ville Distribution Analysis for the Discrimination of Ictal Heart Rate Variability

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***Abstract*—This paper presents a novel method for the discrimination of ictal heart rate variability (HRV). Traditionally, the analysis of the non-linear and non-stationary electrocardiogram (ECG) signal is limited to the time-domain or frequency-domain. This severely limits the quality of features that can be extracted from the ECG signal. In this work, HRV extracted from ECG is analyzed by combining the Matching-Pursuit (MP) and Wigner-Ville Distribution (WVD) algorithms in order to obtain a high quality time-frequency distribution of the HRV signal and to effectively extract meaningful HRV features representative of seizure and non-seizure states. The proposed method is tested on clinical patients and the results demonstrate effective discrimination between ictal HRV features and non-ictal HRV features.**

I. Introduction

Epilepsy is a neurological disorder that is associated with the random occurrence of seizures. During a seizure, the brain endures a transient period of abnormal excessive neural activity which, depending on the type of seizure, can force the patient to endure involuntary alterations in behavior, movement, sensation, or consciousness [1]. Some epileptic patients are able to find relief from their disorder through the use of anti-epileptic drugs or through brain surgery, in which case the epileptogenic focus of the brain is removed [2]. However, approximately 30% of epileptic patients are diagnosed with refractory epilepsy where they do not respond to medication and are not candidates for brain surgery.

Epileptic patients whose treatment options have failed are forced to live with many difficulties such as injuries due to the confusion and loss of muscle control that accompanies some seizures, limited mobility and independence, and emotional and physiological problems. In an attempt to increase the quality-of-life of epileptic patients, much research has been dedicated to developing a device that can detect the onset of seizure episodes before they happen. Such a device is called a seizure onset detector (SOD). SODs have many benefits. For instance, SODs can be used as warning devices to alert patients of imminent seizures so that the patient can take precaution measures before the seizure attack happens, and thus, prevent serious injuries to themselves and those around them. In addition, SODs are gaining more attention as possible seizure control devices. Such detectors can control seizures by initiating anti-epileptic drugs or by selectively stimulating certain parts of the brain when an oncoming seizure is detected [3]. In a hospital setting, such a device would be useful in initiating time-sensitive clinical procedures necessary for the investigation of various epileptic characteristics, such as localizing a patient's epileptogenic focus via ictal single-photon emission computed tomography (SPECT) or functional magnetic resonance imaging (fMRI) [4]. Seizure onset detection is particularly useful to neurologists who usually spend hours analyzing patients' EEG records in an attempt to locate seizure activity. In particular, they greatly reduce the volume of data that must be analyzed.

The manifestation of epilepsy is a fairly complex procedure. In order to gain more insight on how epilepsy develops, doctors often monitor various biosignals of a patient for answers. Electrical biosignals are the most common continuous-time signals studied, and among the most common electrical biosignal is the electrocardiogram (ECG), which represents the recording of electrical activity of the heart. One variable often analyzed when looking at ECG is heart rate variability (HRV), which is defined as the change in the heart's beat-to-beat interval and is often used in the analysis of cardiovascular regulatory mechanisms. Recent advancements in the analysis of HRV in epilepsy reveal that epileptic seizures are accompanied by changes in various autonomic functions such as heart rate (HR) and in the same time unravel causes for sudden unexpected death in epileptic patients (SUDEP) [5], [6]. Furthermore, the estimation of the HRV before, during, and after a seizure provides an indication of the sum of sympathetic and parasympathetic inputs to the heart. Recent investigation points out that epilepsy is frequently associated with ictal tachycardia (ITC) or bradycardia, which, in some cases, precedes the onset of seizures [7]. A review of interictal and ictal cardiac manifestation of epilepsy with focus on HR, HRV, and ECG changes is given in [7].

In [8], HRV is analyzed to differentiate ictal tachycardia from exercise. HRV is analyzed using four methods consisting of: (1) reciprocal high frequency power based on Fast Fourier Transformation, (2) Cardiac Sympathetic Index (CSI), (3) Modified CSI both based on Lorenz plot, and (4) heart rate differential method. It was found that the modicfied CSI was the most accurate method in the detection of ictal

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activity. A set of time- and frequency-domain features and nonlinear parameters based on Poincare plots are extracted and analyzed from the HRV of epileptic patients in [9]. The analysis concluded that ictal HRV parameters differ significantly from baseline HRV. Lagged Poincare plots, autocorrelation, and detrended fluctuation analysis are applied to HRV in [10] in order to analyze the difference in HRV patterns between diabetic and age-matched healthy control subjects. The work in [11] analyzes HRV using Poincare plots and recurrence quantification methods in order to differentiate between normal and abnormal HRV. Biomedical signals are characterized by non-linear time-varying properties making them non-stationary from a statistical point-of-view. However, the majority of analyses carried out on epileptic HRV exploit time-domain or frequency-domain methods. The recent work in [12] demonstrates that the combination of time-variant, frequency-selective, linear and nonlinear analysis approaches can be beneficially used for the analysis of HRV in epileptic patients. The work in [5] demonstrated that signal-adaptive approaches based on Matched Gabor Transform with nonlinear bispectral analysis and Empirical Mode Decomposition with time-variant nonlinear stability analysis show a noticeable difference between specific HRV ictal and non-ictal components.

One of the major shortcomings of existing work on ictal HRV can be highlighted by analyzing the HRV signal itself. HRV signals are nonlinear and non-stationary in nature allowing the frequency content of the signal to vary with time. It is well documented that this variation may be crucial in the important tasks of detection [13]. However, current seizure detectors have limited their analysis of HRV to the time or frequency domains using linear and nonlinear methods. This major limitation restricts the potential of ECG and HRV signals in seizure detection, as well as decreases the quality of features that can be extracted.

Time-frequency (TF) representations are able to localize the signals energy in both time and frequency domain by mapping a one-dimensional signal into a two-dimensional representation. Thus, in an attempt to enhance seizure detection via HRV features, we propose a signal adaptive quadratic time-frequency distribution approach in analyzing HRV based on the combination of the Matching-Pursuit (MP) and Wigner-Ville Distribution (WVD) algorithm. This method enables the extraction of more meaningful features from HRV data, and thus, improves the detection results.

The rest of the paper is outlined as follows. Section II discusses the clinical data that is used for performance evaluation of the proposed analysis technique in this paper. Section III describes the proposed ECG analysis and feature extraction technique. Section IV, illustrates the proposed evaluation techniques on a set of clinical patients. Finally, concluding remarks are given in Section V.

II. Clinical Data

The data used to evaluate the proposed HRV analysis technique in this paper is obtained from the EPILEPSIAE project [14]. The data was recorded during pre-surgical epilepsy monitoring at the Epilepsy Center of the University Hospital of Freiburg in Germany. Ten patients are included in the dataset and each patient has between 98 to 280 continuous EEG and ECG recordings and exhibits between 5 to 22 seizures. The sampling rate of the signals is 256 samples per second with 16-bit resolution. The international $10-20$ system of EEG electrode positions and nomenclature is used for these recordings. All recordings have 19 EEG channels and one-lead ECG recording.

Each seizure's electrographic onset is marked by an experienced electroencephalographer and corresponds to the onset of a rhythmic activity that is associated with a clinical seizure. Each seizure's clinical onset time is also recorded. The data is segmented into one-hour-long records. Records that do not contain a seizure are referred to as non-seizure records and those that contain one or more seizures are referred to as seizure records. Furthermore, the recordings are made in a routine clinical environment, so non-seizure activity and artifacts such as head/body movement, chewing, blinking, early stages of sleep, and electrode pops/movement are present. No constraints regarding the types of seizure are imposed; the data set contains complex partial (CP), simple partial (SP), and secondarily generalized seizures (GS). No form of preprocessing for artifact and noise removal has been performed on the data. Table I summarizes the clinical data used in this work.

TABLE I
SUMMARY OF CLINICAL DATA

Patient Number	Patient Age	Patient Gender	Type of Seizure	Number of Recordings	Number of Seizures
1	36	Male	CP	172	11
2	52	Female	SP	281	8
3	36	Male	SP	121	5
4	43	Female	SP & CP	130	8
5	65	Male	SP, CP, & GS	138	8
6	26	Male	SP	117	22
7	47	Male	CP & GS	98	6

III. ECG Signal Processing

In this section, the set-up for the ECG analysis procedure, shown in Fig. 1, is presented. In the first unit, HRV information is extracted from the ECG signal. In the next two units, the MP-WVD algorithm is applied to the HRV to obtain the time/frequency distribution of the HRV. The last unit extracts relevant features from the time/frequency distribution of the HRV signal to reveal information about seizure and non-seizure states.

A. HRV Extraction

This section presents the different steps required to obtain the HRV from raw ECG. The steps are illustrated in Fig. 2.

In the first step, the problem of baseline wander in the ECG data is addressed. ECG baseline correction in this work is done via a robust and computationally efficient iterative algorithm termed Baseline Estimation and Denoising with

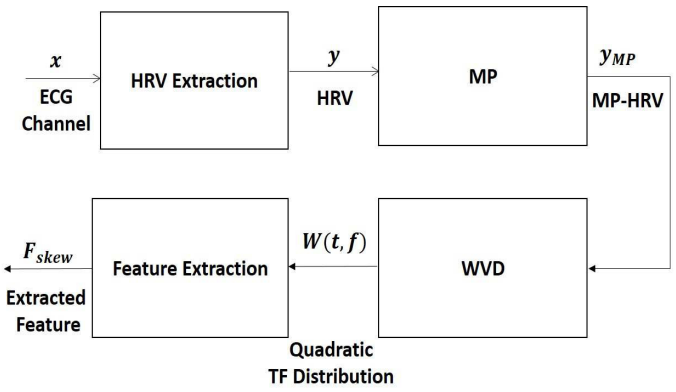

Fig. 1. An illustration of the ECG signal analysis procedure

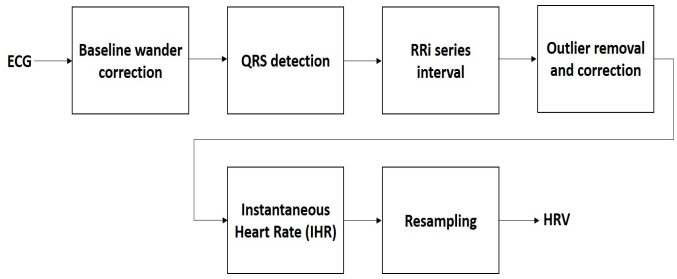

Fig. 2. HRV extraction process.

Sparsity (BEADS) [15]. Next, a QRS detection algorithm is implemented to detect QRS complexes and localize R waves. The algorithm works by searching for local maxima that are above a certain predefined threshold value. The threshold value ensures that the R-peaks are detected instead of the P- and T-wave maxima. Once an R-peak is detected, the algorithm waits for a period of Δ_R seconds before searching for a consecutive R-peak. The wait period is adopted to avoid misclassification due to noise. The R peaks are taken as the location of the R points. Next, the time duration between consecutive R-peaks is used to represent the heart's beat-to-beat interval, known as the RR interval time series, RRi.

The next step in the HRV extraction stage is the removal of outliers from the RRi data. Outliers may exist in the RRi due to QRS missed detections, false detections ectopic beats, or other random-like physiological disturbances. In general, outliers are defined as values which are not within a specified limited interval. In this work, outliers are defined as [16]

$$O(n) = \begin{cases} RRi(n) \quad \text{if} \quad RRi(n) < 1^{st} \text{ quartile}(RRi) - \\ \qquad\qquad\qquad \text{interquartile\_range}(RRi) \times \eta \\ \qquad \text{or} \\ RRi(n) \quad \text{if} \quad RRi(n) > 3^{rd} \text{ quartile}(RRi) + \\ \qquad\qquad\qquad \text{interquartile\_range}(RRi) \times \eta, \end{cases} \tag{1}$$

where O is the outlier, $0 < n \leq \text{length}(RRi)$, and η is a constant. For our data, η is chosen to be 7. Once the outliers are identified, they are removed and the missing data is spline interpolated.

An instantaneous heart rate (IHR) signal is obtained by taking the inverse of the RRi signal. The IHR signal is not uniformly sampled. In the case of time-domain analysis, it is not an issue; however, time-frequency analysis assumes the signal to be uniformly sampled. Uniform sampling is carried out through the method of linear interpolation to obtain a new uniform sampling rate of 20 Hz. The resulting signal constitutes the HRV signal.

B. MP-WVD Algorithm

This section outlines the methods used to generate a high-quality TF distribution of the HRV signal.

The WVD is a powerful quadratic TF distribution algorithm that satisfies several desirable mathematical properties; namely, it is real valued, it preserves time and frequency shift information contained in the signal of interest, it satisfies the marginal properties, the frequency integral of the WVD corresponds to the signal's instantaneous power, and the instantaneous frequency can be estimated from the first moment of the WVD [17]. Although the WVD has good theoretical properties, its major drawback is that it can suffer from interference terms between the components of a multi-component signal. These interference terms oscillate in the TF plane and indicate activity which does not exist, leading to erroneous visual interpretation of a signal's TF structure. Variations of the WVD have been proposed in the literature to reduce the effect of the interference terms, i.e., pseudo-WVD and the smoothed-pseudo-WVD). However, these windowed methods present a trade-off between TF resolution and cross-term reduction and they only reduce the interference terms, they do not *eliminate* them. Because interference terms in the WVD appear only in multi-component signals, we implement an algorithm that decomposes the HRV signal into a sum of mono-component signals. This decomposition can be carried over by employing the MP algorithm.

The MP algorithm decomposes a signal into a sum of atoms from a given dictionary. In this work, the Gabor atom dictionary is used because Gabor atoms are mono-component signals per definition. Therefore, the application of the WVD on a signal that has been decomposed via MP with Gabor atoms presents excellent time-frequency resolution and does not yield any interference terms.

The Gabor atom can be expressed in terms of the modulated Gaussian function $g(t) = e^{-\pi t^2}$. The Gabor atom assumes the expression [18]

$$g(t) = Ae^{-\pi\left(\frac{t-u}{s}\right)^2} \cos\left(w(t-u) + \varphi\right), \tag{2}$$

where s represents a scaling factor, w denotes the frequency modulation, u stands for the translation factor, φ models the phase, and A is a normalization factor such that $\|g(t)\| = 1$. The Gabor atom dictionary is denoted by D and can be written as:

$$D = \left[g_1(t), g_2(t), \cdots g_M(t)\right], \tag{3}$$

where M denotes the number of atoms in the dictionary. The

MP decomposition of the HRV signal $y(t)$ is expressed as:

$$y(t) \approx \sum_{n=1}^{N} a_n g_n(t) + R_N, \tag{4}$$

where $M \gg N$, a_n is a weighting coefficient, and R_N denotes the residual. The MP decomposes $y(t)$ by finding the best orthogonal projections amongst a set of basis functions from the dictionary D that matches the structure of $y(t)$. The result is a finite number of basis functions organized in a decreasing order of energy. The standard MP algorithm is an iterative algorithm and is outlined in the following steps.

Step 1: Initialize $n = 1$ and $R_0 = y(t)$.
Step 2: Compute $|\langle R_{n-1}, g_i(t)\rangle|$ for all $g_i(t) \in D$.
Step 3: Find $g_n^* = \underset{g_i(t)}{\text{argmax}} |\langle R_{n-1}, g_i(t)\rangle|$.
Step 4: Compute the weighting coefficient: $a_n = \langle R_{n-1}, g_n^*\rangle$.
Step 5: Compute the new residual: $R_n = R_{n-1} - a_n \cdot g_n^*$.
Step 6: Remove g_n^* from D.
Step 7: If $n = m$ or $\epsilon \leq$ threshold, stop, where m is a given iteration number and ϵ is the energy of the residual R_n; otherwise set $n = n + 1$ and go to **Step 2.**

Let the MP-decomposed HRV signal be denoted by $y_{MP}(t)$. The WVD of $y_{MP}(t)$ is given by

$$W(t,f) = \int_{-\infty}^{+\infty} y_{MP}\left(t + \frac{\tau}{2}\right) y_{MP}^*\left(t - \frac{\tau}{2}\right) e^{-j2\pi f\tau} d\tau, \tag{5}$$

where the values of $W(t,f)$ are stored into an $\mathrm{L}_t \times \mathrm{L}_f$ matrix and the asterix symbol used as a superscript indicates the operation of complex conjugation.

C. Feature Extraction

There are many features that can be extracted from the TF distribution of the HRV signal to characterize the seizure and non-seizure phenomena, such as central frequency, mean, skewness, kurtosis, and Shannon entropy [19], [17] . In this work, the skewness of MP-WVD HRV signal is chosen because based on our experiential analysis, skewness best characterizes changes in epileptic HRV. Skewness is a time-domain feature that can be translated to the TF domain as follows [19]

$$F_{skew} = \frac{1}{(L_t L_f - 1)\sigma_{TF}^3} \sum_{i=1}^{L_t} \sum_{j=1}^{L_f} \left(W[i,j] - \mu_{TF}\right)^3, \tag{6}$$

where μ_{TF} and σ_{TF} are the mean and standard deviation of $W(t,f)$ and are given by

$$\mu_{TF} = \frac{1}{L_t L_f} \sum_{i=1}^{L_t} \sum_{j=1}^{L_f} W[i,j] \tag{7}$$

and

$$\sigma_{TF}^2 = \frac{1}{L_t L_f} \sum_{i=1}^{L_t} \sum_{j=1}^{L_f} \left(\mu_{TF} - W[i,j]\right)^2, \tag{8}$$

respectively.

IV. Results and Discussion

In this section, we illustrate the effectiveness of the proposed ECG analysis technique in the discrimination of ictal HRV.

The HRV of a particular patient's (patient 1) one-hour ECG data is depicted in Fig. 3. The blue signal corresponds to the non-seizure HRV data and the red signal is the seizure HRV data. The seizure starts at 2638 seconds and lasts until 2693 seconds. This particular patient observes a sharp decrease of HRV after the onset of the seizure, reaching 0.95 beats per second (bps). The MP-WVD of a segment of the HRV taken 20 seconds prior to the seizure onset and 20 seconds after the seizure offset is depicted in Fig. 4. The HRV time-domain signal is also shown in Fig. 4 for discussion purposes. In this segment, the seizure onset and offset are marked by arrows. Approximately ten seconds after the onset of the seizure, activity in the low-frequency band (0.04-0.15 HZ) is noticed, followed by a sharp decrease of spectral activity in the very low frequency band (0.0033-0.04 Hz). This activity coincides with the decrease in HRV that occurs 33 seconds after the onset of the seizure. Also, Fig. 4 is of high resolution and does not contain any interference terms. The skewness, calculated from the MP-WVD of the HRV shown in Fig. 3, is depicted in Fig. 5. The skewness of the HRV decreases after the onset of the seizure and resumes normal activity after the seizure episode has passed. Visually looking at the graph of the skewness feature, we are able to detect the unusual activity from the background features.

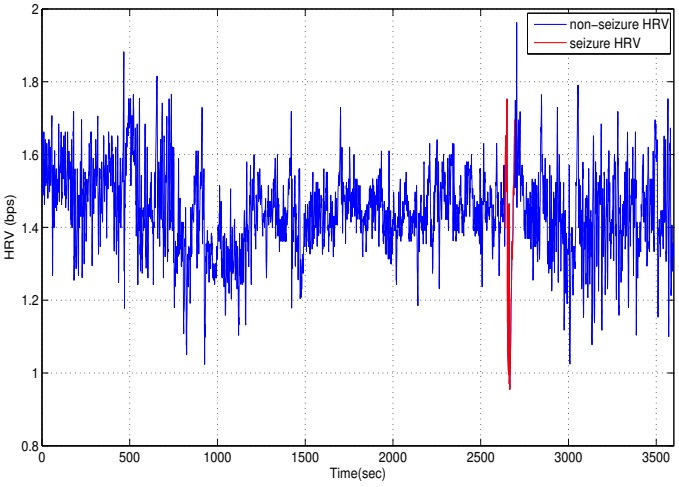

Fig. 3. HRV of patient 1.

The success of seizure onset detection systems greatly depends on the type of features extracted from the data. As seen from the clinical examples shown in Fig. 3 - Fig. 5, the proposed MP-WVD HRV processing technique allows for the effective analysis of HRV so that discriminatory features can be extracted from HRV.

V. Conclusions and Future Research

In this work, we describe a novel algorithm for the discrimination of ictal HRV via the combination of the MP

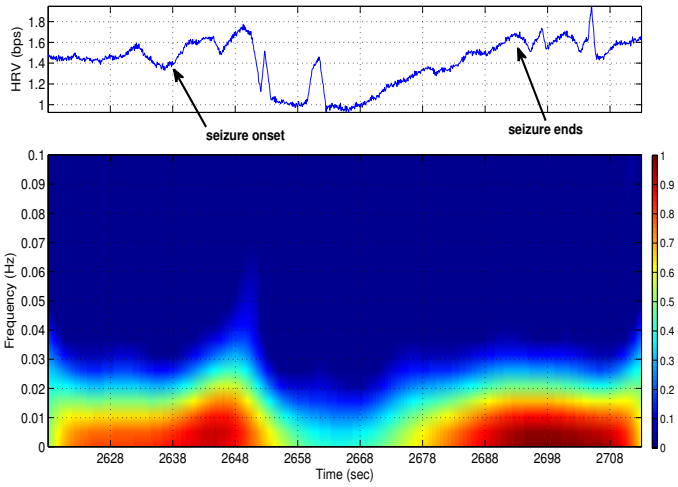

Fig. 4. Segment of MP-WVD of the HRV of patient 1. Color bar in $(\text{bps})^2$.

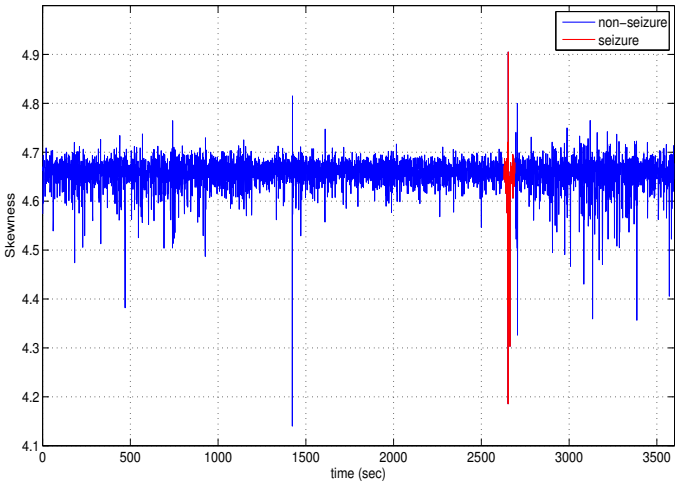

Fig. 5. Skewness of the MP-WVD HRV of patient 1.

and WVD algorithms. The HRV is decomposed into mono-components signals via the MP algorithm prior to applying the WVD algorithm. The time-frequency analysis of the HRV signal allows for a deeper and more relevant decomposition of the non-linear and non-stationary signals, thus extracting more informative features. The ability to extract discriminatory ictal and non-ictal HRV features allows for better detection results. The proposed method to analyze the ECG signal has demonstrated great potential for use in detection systems that can be used for medical intervention and warning systems, which is a topic of our future research.

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