International Journal of Cardiology 222 (2016) 504–508

Contents lists available at ScienceDirect

International Journal of Cardiology

journal homepage: www.elsevier.com/locate/ijcard

Atrial fibrillation classification and association between the natural frequency and the autonomic nervous system

Nurul Ashikin Abdul-Kadir, Norlaili Mat Safri *, Mohd Afzan Othman

Department of Electronic and Computer Engineering, Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia

ARTICLE INFO

Article history:
Received 28 May 2016
Accepted 28 July 2016
Available online 29 July 2016

Keywords:
Atrial fibrillation
Autonomic nervous system
Dynamic system
Heart rate variability
Natural frequency

ABSTRACT

Background: The feasibility study of the natural frequency (ω) obtained from a second-order dynamic system applied to an ECG signal was discovered recently. The heart rate for different ECG signals generates different ω values. The heart rate variability (HRV) and autonomic nervous system (ANS) have an association to represent cardiovascular variations for each individual. This study further analyzed the ω for different ECG signals with HRV for atrial fibrillation classification.

Methods: This study used the MIT-BIH Normal Sinus Rhythm (*nsrdb*) and MIT-BIH Atrial Fibrillation (*afdb*) databases for healthy human (NSR) and atrial fibrillation patient (N and AF) ECG signals, respectively. The extraction of features was based on the dynamic system concept to determine the ω of the ECG signals. There were 35,031 samples used for classification.

Results: There were significant differences between the N & NSR, N & AF, and NSR & AF groups as determined by the statistical *t*-test ($p < 0.0001$). There was a linear separation at 0.4 s^{-1} for ω of both databases upon using the thresholding method. The feature ω for *afdb* and *nsrdb* falls within the high frequency (HF) and above the HF band, respectively. The feature classification between the *nsrdb* and *afdb* ECG signals was 96.53% accurate.

Conclusions: This study found that features of the ω of atrial fibrillation patients and healthy humans were associated with the frequency analysis of the ANS during parasympathetic activity. The feature ω is significant for different databases, and the classification between *afdb* and *nsrdb* was determined.

1. Introduction

The heart beat duration for the next beat varies and is related to the autonomic nervous system (ANS). Each heart beat shows the condition of the heart and represents the physical and psychological states for a particular person. The normal heart rate is 60 beats per minute (bpm) during rest, up to 100 bpm during any physical activity, and up to 200 bpm during exercise [1]. In atrial fibrillation (AF), the heart beats at up to 600 bpm (atrium pulses) with a ventricular rate of more than 100 pulses per minute [1,2]. The ANS activity and heart rate have a relation because the ANS activity automatically controls the heart through sinoatrial (SA) node [3]. The ANS controls the heart rate (HR), heart rate variability (HRV), involuntary functions such as breathing, the blood pressure, and the reaction of withdrawing hands from a hot surface. The HRV can be measured to gain insight into the auto regulation function. In frequency domain analysis, four bands or frequency ranges - ultra low, ULF; very low, VLF; low, LF; and high, HF - represent time scales of cardiovascular variations. The frequency ranges for those four frequency bands are ULF (0.0001 Hz–0.003 Hz), VLF (0.003 Hz–0.04 Hz), LF (0.04 Hz–0.15 Hz) and HF (0.15 Hz–0.4 Hz) [4], named circadian, myogenic, sympathetic and parasympathetic, respectively. This measurement is according to the European Cardiologic Society and North American Society for Stimulation and Electrophysiology standard [4].

The relationship between the HRV and the ANS imbalance has been shown by several studies, of which the HRV for AF patients has been explored [5]–[11]. The HRV for a patient who suffers from irregular heart rate or multiple ectopic beats is difficult to interpret compared to a patient who suffers from sinus arrhythmias (e.g., AF) [12]. When LF is greater than HF, it indicates a sympathetic type [5,6], referred to as Type A, i.e., a higher AF recurrence [7]. On the other hand, a decrease in LF power and an increase in HF indicate an increase in the parasympathetic vagal tone, i.e., the onset of paroxysmal AF [5,6] referred to as Type B. [11] found an increase in the HF band for AF patients, and [8] showed a relation between the AF rate and RR variability in AF patients. [8] also found a higher correlation between AF rates and RR-variability in AF patients. The extracted features from the HRV of the AF signal were able to differentiate the sympathetic and parasympathetic before AF attacks [9]. Study [10] achieved 100% sensitivity for AF detection based on HRV.

The HRV can be measured either using parametric (time-domain) or non-parametric (frequency-domain) analysis. The parametric method

* Corresponding author.
E-mail address: norlaili@utm.my (N. Mat Safri).

http://dx.doi.org/10.1016/j.ijcard.2016.07.196
0167-5273/

is a method of testing a hypothesis that requires the user to assume a particular model for the distribution of data or define the data in terms of a parameter. In the parametric method, the individual spectra of short-term monitoring, such as the RR-interval [13–16], are measured. The RR-interval is also known as the NN-interval (normal-to-normal sinus interval). Several statistical methods can be calculated based on the NN-interval, for example, the standard deviation of all NN-intervals (SDNN) [8,17], the mean standard deviation of all NN-intervals (SDNN index) [17], the standard deviation of average NN-intervals (SDANN), the root-mean-square value of the square differences between neighboring NN-intervals (RMSSD) [8,13,17], the standard deviation of neighboring NN-interval differences (SDSD) [17], the count of coupled neighboring NN-intervals differing by more than 50 ms in length (NN 50), and NN 50 divided by the total count of NN-intervals (p NN 50) [8, 17]. The accuracy achieved by [13] was 98.44% using RMSSD. The transition between AF and the sinus rhythm based on the RR-interval achieved 96.1% sensitivity and 98.1% specificity [14]. The RR characteristic of the AF rhythm can provide 92% sensitivity in detecting AF [15]. [16] describes an AF automatic detection algorithm based on the RR-interval time series with a sensitivity and specificity of 94.4% and 95.1%, respectively. Moreover, the HRV computed by [17] obtained an accuracy of 99.16%.

The second-order dynamic system (SODS) method is a parametric method. An SODS is described in terms of differential equations. Three features can be determined from the SODS method by using five time-domain values (x_1, x_2, x_3, x_4 and x_5) of an ECG signal: natural frequency (ω), damping coefficient (ξ) and forcing input (u). The algorithm of the natural frequency has been studied by [18,19] for ventricular arrhythmias, achieving sensitivities of 98.1% and 94.1% and specificities of 97.7% and 95.2%, respectively. The non-parametric method, different from the parametric methods, results in spectra of the frequency domain that are commonly used called Fourier transform [20]. A classification accuracy of 97.92% was achieved in the study. The geometrical method is also a non-spectral method. For example, the histograms of the NN-interval showed the HRV index and the triangular interpolation of NN intervals (TINN) [21] with $p < 0.001$. The HRV index method is the total count of NN-intervals divided by the histogram height. TINN is a triangle-based length obtained by the triangular interpolation of a histogram using the smallest square method. Study [9] used both parametric and non-parametric methods and obtained a 94.7% accuracy rate.

In this study, we explore the AF classification and the association of the natural frequency of SODS towards HRV frequency analysis, which is related to ANS specifically for atrial fibrillation patient and healthy human ECG signals. We hypothesized that the natural frequencies for an AF patient and the NSR of a healthy human can be different. Therefore, the extraction of the natural frequency using SODS was analyzed for AF patients and healthy human ECG signals.

2. Methods

2.1. Subjects

We used two ECG databases from the Physiobank ECG Archive: the Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) Normal Sinus Rhythm Database (*nsrdb*) and the MIT-BIH Atrial Fibrillation Database (*afdb*) [22]. The databases contained 18 and 23 ECG records, respectively. The *nsrdb* contains ECG records for healthy humans, while *afdb* contains ECG records for AF patients. The sampling rates for the databases are 128 Hz and 250 Hz, respectively. Three types of ECG signals were used, namely, the normal sinus rhythm of a healthy human (NSR), the normal sinus rhythm of an atrial fibrillation patient (N) and an atrial fibrillation rhythm (AF). The NSR was collected from *nsrdb*, while N and AF were collected from *afdb*. ECG records of twelve subjects from *afdb* were used in this study, providing 24 ECG records from AF patients, together with another twelve ECG records from *nsrdb*, for a total of 36 ECG records were used. Each record contained 11,677 episodes.

2.2. ECG pre-processing stage

The data were sampled by using a 4 s window size for the extraction process. There are two different sampling frequencies of the recorded ECG signals for *afdb* and *nsrdb*. Therefore, the ECG records of *nsrdb* were rescaled to 250 Hz, the same sampling frequency as *afdb*. The greater sampling rate can avoid the amplitude reduction of the P-wave [23–25]. The filter used in this study is a Butterworth band-pass, with a pass-band of 1 to 30 Hz [26]. The ECG signal used in this study contained 11,677 episodes for each type (NSR, N and AF), for a total of 35,031 samples used for analysis. The window size is 4 s [27], and it was shifted by 1 s increments [28] by using a moving average filter [29]. Further description of the extraction process is provided in the following section.

2.3. ECG feature extraction process

The feature extraction of the ECG signals was based on the second-order dynamic system (SODS) method. Further description of the algorithm is provided in a previous study [30]. Eq. (1) shows the second-order differential equations (SODE) for describing the ECG system. The algorithm describes the SODS method.

$$\frac{d^2}{dt^2}x(t) + 2.\zeta.\omega\frac{d}{dt}x(t) + \omega^2.x(t) = \omega^2.u(t) \tag{1}$$

Three features are extracted from algorithm (1): the natural frequency (ω), damping coefficient (ξ), and forcing input (u). The algorithm of ω is described in Eq. (2). Further derivation of ξ and u is provided in [30]. ω determines how quickly the ECG system oscillates during any transient response, and $x(t)$ is the ECG signal with respect to time, t. Case studies of ECG extraction using SODS are provided in [27,31,32].

$$\omega = \sqrt{\frac{\frac{d^2}{dt^2}x(t).\frac{d^4}{dt^4}x(t) - \left(\frac{d^3}{dt^3}x(t)\right)^2}{\frac{d}{dt}x(t).\frac{d^3}{dt^3}x(t) - \left(\frac{d^2}{dt^2}x(t)\right)^2}} \tag{2}$$

2.4. Classification using thresholding method

The natural frequency features that were extracted for NSR, N and AF are classified into healthy human and patient classes. The classification is according to a linear separation that is based on the thresholding method for separation into two classes. The algorithm of separation is to determine a linear line, a threshold (*Th*), between two different classes, according to Eq. (3). The threshold value, *Th*, is the linear line that separates the two classes. max*aveAF* refers to the average maximum value of the patients, while min*aveNSR* refers to the average minimum value of the healthy humans.

$$Th = \max aveAF + (\min aveNSR - \max aveAF)/2 \tag{3}$$

The distribution of all ECG signals was plotted as the average value. The values of min*aveNSR* and max*aveAF* were used to calculate a suitable threshold value for classification between healthy humans (NSR) and atrial fibrillation patients (N and AF). The min*aveNSR* and max*aveAF* values were 0.5 s^{-1} and 0.3 s^{-1}, respectively, so *Th* is 0.4 s^{-1}. Based on the threshold value, the natural frequency values are separated into true positive (*TP*), false negative (*FN*), true negative (*TN*), and false positive (*FP*). The extracted natural frequency values above *Th* are the negative condition (not being sick or healthy), and the values below *Th* are the positive condition (being sick or unhealthy). Therefore, *FN* is a condition of an unhealthy feature that is determined as healthy, *TN* is a condition of a healthy feature that is determined as healthy, *TP* is a condition of an unhealthy feature that is determined as unhealthy, and *FP* is a condition of a healthy feature that is determined as unhealthy. The sensitivity is the true positive rate, i.e., the unhealthy ECG signals (AF) correctly identified as being sick, while the specificity is the true negative rate, i.e., the healthy ECG signals (NSR) correctly identified as not being sick. The algorithms for the sensitivity (*Se*), specificity (*Sp*) and accuracy (*Acc*) are shown in Eqs. (4), (5) and (6), respectively, and further discussion is provided in the following section.

$$Se = \frac{TP}{TP + FN} \tag{4}$$

$$Sp = \frac{TN}{TN + FP} \tag{5}$$

$$Acc = (Se + Sp)/2 \tag{6}$$

3. Results and discussion

3.1. Natural frequency of second-order dynamic system

The MIT-BIH Normal Sinus Rhythm Database (*nsrdb*) record number #16265 was used for the sampling identification [22,33]. The selected ECG signal started at 08:05:00 (minutes 60 s) and extended to 08:05:10