Real-time detection of imminent ventricular fibrillation using mean and standard deviation of beat-to-beat HRV

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***Abstract*— It is estimated that 50% of all cardiovascular deaths are caused by a sudden cardiac arrest (SCA), which represents 15% of global mortality, and its main cause is ventricular fibrillation (VF). Therefore, it is of interest to design new methods capable to detect changes in heart rate (HR or RR interval) that could announce the beginning of an imminent fibrillation. In this work, an effective novel indicator, based on mean and standard deviation of Heart Rate Variability (HRV), was studied and used to develop an algorithm that predicts imminent VF with 100% sensitivity and 100% specificity. The study was based on 65 RR intervals signals. The algorithm's simplicity provides a quick-to-use implementation in a micro controller unit (MCU) for real-time VF detection, allowing its application in a variety of medical devices with electrocardiogram (ECG) modules.**

***Keywords*— Ventricular Fibrillation, Heart Rate Variability, Imminent Ventricular Fibrillation, Mean, Standard Deviation.**

***Resumen*— Se estima que el 50% de todas las muertes cardiovasculares son causadas por un paro cardíaco repentino (PCR), el cual representa el 15% de la mortalidad global, y su causa principal es la fibrilación ventricular (FV). Por lo tanto, es interesante diseñar nuevos métodos capaces de detectar cambios en la frecuencia cardíaca (intervalo FC o RR) que pueda advertir el comienzo de una fibrilación inminente. En este trabajo, se estudió un indicador novedoso eficaz, basado en la media y la desviación estándar de la Variabilidad de la Frecuencia Cardíaca (VFC), y se utilizó para desarrollar un algoritmo que predice una FV inminente con una sensibilidad y una especificidad del 100%. El estudio se basó en 65 señales de intervalos RR. La simplicidad del algoritmo proporciona una implementación rápida en una unidad de microcontrolador (MCU) para la detección de FV en tiempo real, lo que permite su aplicación en una variedad de dispositivos médicos con módulos de electrocardiograma (ECG).**

***Palabras clave*— Fibrilación ventricular, variabilidad del ritmo cardíaco, fibrilación ventricular inminente, media, desviación estándar.**

I. Introduction

An electrocardiogram (ECG) describes the electrical activity of the heart, namely heartbeat, recorded by electrodes placed on the body surface. The measured voltage variations display a series of waveforms. Signal changes, such as disturbances or abnormalities in the waves morphology and timing, may reflect underlying heart complications and diseases that can be diagnosed and treated based on the ECG signal [1], see Figure 1(a).

Ventricular Fibrillation (VF) is a shockable cardiac arrest rhythm that occurs when different ventricle fibers attempt to contract uncoordinated [2]. This abnormal contraction can be identified in an ECG due to asynchronized beats, showing an electrical signal with no identifiable P waves, QRS complexes and T waves. Several methods have been studied to identify and characterize VF waves including wavelets and mother rotors [3], [4], shown to be different between human and animal hearts of different size [5]. This rhythm is lethal unless the heart is defibrillated [2].

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Many VFs are preceded by ventricular tachycardia, which is an indicator used by defibrillating pacemakers in order to prepare the discharge of a defibrillator shock. However, the time in which there is an increase in heart rate prior to a VF is short and its detection might not provide enough anticipation. It is of interest to find an indicator of an incoming onset independent of tachycardia.

Heart Rate Variability (HRV) gives information on the variation of the time interval between heart beats [1]. It is also called RR variability as each heart beat corresponds to an R peak in the ECG signal. In this study, HRV is analyzed using time-domain methods on ECG and preprocessed RR signals (NN). Two variables were studied from the beat-to-beat or NN intervals: the Average of the NN intervals (AVNN) and the Standard Deviation of the NN intervals (SDNN).

The aim of this study is to propose a novel and simple algorithm for the detection of VF onsets that can be implemented in a micro controller unit (MCU) for use in real-time. This motivation arose because 50% of all cardiovascular deaths are caused by a sudden cardiac arrest (SCA), which

TABLE I
DEMOGRAPHIC DATA OF SAMPLE POPULATION.

Database	Age. Median (Range)	Gender	Myocardial infarct	Cardio myopathy
Control I	45(21-77)	M:19% F:81%	0%	0%
Control II	34(20-50)	M:28% F:72%	0%	0%
Pre-VF	57.5(32-73)	M:80% F:20%	45%	55%

represents 15% of global mortality [6] and its mainly caused by Ventricular Fibrillation (VF) [7]. Therefore, it is relevant to design a method capable of detecting changes in heart rate (HR or RR interval) that could announce the beginning of an imminent fibrillation. Preliminary experiments with 65 RR intervals, based on mean and standard deviation of HRV, suggest that the proposed methodology is a powerful tool to the detection of VF onsets with 100% sensitivity and 100% specificity.

The remaining paper is organized as follows. Section II describes the methodology proposed. Then, in Section III, the methodology is applied to real ECG data. Discussion, conclusions and future works, are finally reported in sections IV and V.

II. METHODOLOGY

A. Databases used

The data used for this analysis consisted on a total of 65 RR interval signals: 45 control RR and ECG series from two different databases and 20 pre-VF RR series.

1) **Control patients I:** the RR series of 27 patients who had never suffered any cardiac malfunctioning were taken from "HMS-MIT-FFMS database" [8]. Subjects include 5 men between 23 and 74 years old, and 22 women between 21 and 77 years old.
2) **Control Patients II:** Eighteen RR series were calculated from the "The MIT-BIH Normal Sinus Rhythm Database" [9] ECG signals (Figures 3 and 4). Subjects did not have any significant arrhythmias and included 5 men, aged 26 to 45, and 13 women, aged 20 to 50.
3) **Pre-VF signals from fibrillating patients:** 20 patients who had suffered at least one VF, and their RR series was measured before the outbreak of a spontaneous episode of VF. The last 1024 heart beats before the VF were considered for each patient, obtained from "Spontaneous Ventricular Tachyarrhythmia Database Version 1.0 from Medtronic, Inc." [10]

The sample population demography is summarized in Table I

B. Selection of detection indicator

For all data management and analysis during this work, as well as for all methods created, MatLab R2016a was used.

When evaluating RR signals as a function of time for control patients (Figure 1(b)), most signals were similar, oscillating around a mean value; however, when evaluating it for pre-VF subjects, signals showed a high variability between each pre-VF patient. Even though using RR signals for evaluating possible indicators has the advantage of a significant difference in behavior between control and pre-VF patients, it cannot be used to extract general behaviors for pre-VF patients and obtain a global detection rule.

In each one of the 65 RR series considered, mean and standard deviation were calculated for the RR array. Each signal $\boldsymbol{X}$ was divided into smaller extracts with a moving rectangular window $\boldsymbol{\Omega}$, calculating AVNN and SDNN of each signal section (Equations (1) to (3) respectively). Different window lengths and overlaps were evaluated, finding a 50 beats window with one beat step (Figure 1(c)) as the optimal combination.

$$AVNN = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{X}_i \boldsymbol{\Omega}_i \tag{1}$$

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}\left|\boldsymbol{X}_i\boldsymbol{\Omega}_i - \frac{1}{N}\sum_{i=1}^{N}\boldsymbol{X}_i\boldsymbol{\Omega}_i\right|^2} \tag{2}$$

$$\Omega = \Omega_0\left(n - \frac{N-1}{2}\right) \quad 0 \le n \le N-1 \tag{3}$$

The proportional beat-to-beat variation of AVNN and SDNN as the window approaches the onset showed visually noticeably differences. For its calculation, with each new displacement of the window, AVNN and SDNN are calculated, and their difference with the previous AVNN and SDNN are respectively defined as ΔAVNN % and ΔSDNN% (Equations (4) and (5))

$$\Delta AVNN\%_n = \frac{(AVNN_n - AVNN_{n-1})}{AVNN_{n-1}} \tag{4}$$

$$\Delta SDNN\%_n = \frac{(SDNN_n - SDNN_{n-1})}{SDNN_{n-1}} \tag{5}$$

When plotting beat-to-beat ΔAVNN% and ΔSDNN% for pre-VF patients, significant peaks were found, which did not exist for control patients plots, showing that ΔAVNN% and ΔSDNN% were promising indicators (Figure 1(d)).

C. Detection Method

The detection method designed evaluates two thresholds in each beat-to-beat ΔSDNN% and ΔAVNN%.The algorithm is executed with each new beat (Figure 2), firstly adding the new beat to the 50-samples buffer and removing the oldest one. Continuously, the mean and standard deviation are calculated, and compared with the prior mean and standard deviation values respectively. The $\Delta SDNN\%_n$ obtained is checked against its threshold (T_{SDNN}) and if higher, the $\Delta AVNN\%_n$ is checked against its corresponding threshold (T_{AVNN}). If this second condition is met as well, the signal is detected as pre-VF.

D. Evaluation of significance

A Student's t-test was made with MS. Excel™(2016) Data Analysis Toolkit to compare the values obtained from normal and pre-VF ΔAVNN% and ΔSDNN% minus their respective thresholds. This test allows to call significance between the normal and pre-VF values obtained.

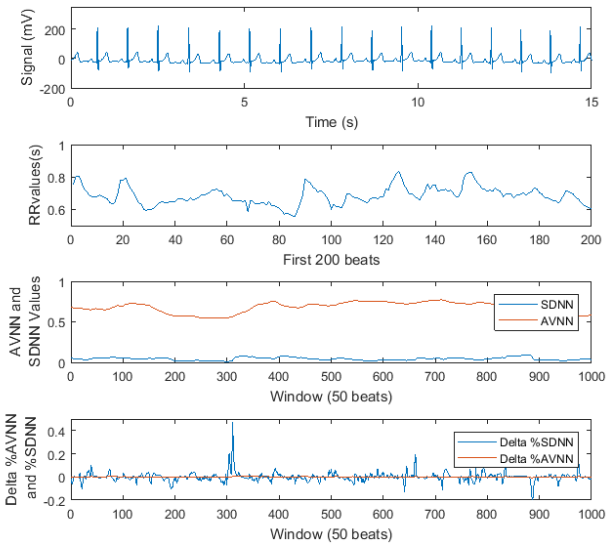

Fig. 1. Example of analysis done a control ECG signal; (a) Raw ECG signal from database [9]. First 15 seconds are shown; (b) RR values for first 200 beats; (c) Average AVNN and SDNN calculated with windows containing 50 RR values; (d) Difference in AVNN and SDNN between consecutive windows. The difference was shown to be more significant in ΔSDNN% rather than ΔAVNN%, which is not observable.

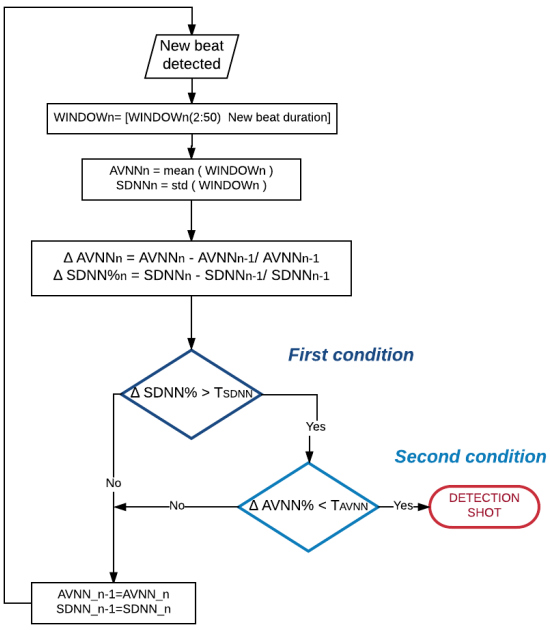

Fig. 2. Flow diagram for VF detection method.

III. Results

A. Analysis of ΔAVNN% and ΔSDNN% values

The maximum ΔSDNN% was identified for each subject and their respective ΔAVNN%, corresponding to the same RR interval, was analyzed (Figures 3 and 4). The ΔSDNN% was taken as the main parameter because its absolute values are higher and one can better appreciate its changes in comparison to ΔAVNN%. The latter's absolute value varies more evenly between patients and conditions.

All pre-VF signals show positive peaks as maximum variation for ΔSDNN% values. In 18 patients, the ΔAVNN% value is negative and in the 2 cases where it is not, the positive ΔAVNN% has the lowest absolute value in comparison to the other peaks. Control patients, however, show a more even distribution of module and sign of both parameters.

B. Threshold Estimation

A rough approximation of the thresholds was done from the previously noted characteristics. The estimation of T_{SDNN} was done considering the maximum ΔSDNN% for all 65 patients. A boxplot was made separating signals into two groups and evaluating the maximum value of ΔSDNN% for each signal (Figure 3). The distributions of groups are distinguishable, suggesting this is a good indicator to identify each group. A starting threshold T_{SDNN} of 0.35 was chosen, requiring a higher value in order to met the criteria. It is clear from Figure 3 that this threshold alone would not separate correctly all signals.

The second necessary threshold was estimated from a boxplot of ΔAVNN% value at the beat corresponding to maximum ΔSDNN% (Figure 4). A starting threshold T_{AVNN} of 0 was chosen, in this case requiring a lower value to meet to criteria.

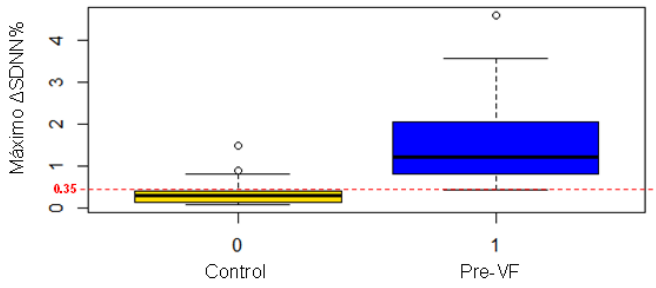

Fig. 3. Maximum ΔSDNN% for non-fibrilating and fibrilating patients

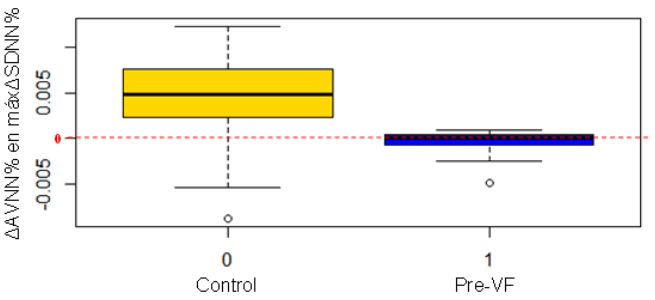

Fig. 4. ΔAVNN% at the beat with maximum ΔSDNN%, for non-fibrilating and fibrilating patients

An optimization was run around the previously explained tentative thresholds, to find which values minimized the number of pre-VF signals incorrectly detected as normal and the number of normal RR signals incorrectly detected as pre-VF.

The limits for the tested values of T_{AVNN} were chosen as -0.002 and -0.007. A value greater than zero already showed a loss of specificity with a T_{SDNN} fixed at 0.35, while a value lower than -0.007 already showed a loss of sensitivity.

In the case of T_{SDNN}, the limits were chosen as 0.33 and 0.38. A value lower than 0.33 already showed a loss of

TABLE II
FALSE POSITIVES AND NEGATIVES OBTAINED WITH THE OPTIMIZATION (FP:FN)

FP:FN	T_{AVNN}					
T_{SDNN}	-0.007	-0.006	-0.005	-0.004	-0.003	-0.002
0.33	1 : 4	1 : 1	1 : 0	2 : 0	4 : 0	4 : 0
0.34	1 : 4	1 : 1	1 : 0	2 : 0	4 : 0	4 : 0
0.35	0 : 4	0 : 1	0 : 0	1 : 0	3 : 0	3 : 0
0.36	0 : 4	0 : 1	0 : 0	1 : 0	2 : 0	2 : 0
0.37	0 : 4	0 : 1	0 : 0	1 : 0	2 : 0	2 : 0
0.38	0 : 5	0 : 2	0 : 1	1 : 1	1 : 1	1 : 1

specificity with a T_{AVNN} fixed at 0.0, while a value higher than 0.38 already showed a loss of sensitivity.

In the main optimization, we tested thresholds in every beat of all signals. If a beat met both criterias, the signal was considered positive. If no beat met both criterias, the signal was considered negative. We looked for the best combination of T_{SDNN} and T_{AVNN}, evaluating the number of false positives and false negatives. T_{SDNN} was varied between 0.33 and 0.38 with a step of 0.1, and T_{AVNN} was varied between -0.002 and -0.007 with a step of 0.001. The results for these 36 iterations can be seen in Table II.

The best performance obtained detected no false positives and no false negatives. The optimal thresholds were found to be:

ΔAVNN% Threshold: $T_{AVNN} = -0.005$

ΔSDNN% Threshold: $T_{SDNN} = 0.36$

These thresholds were applied both to the 45 normal signals, or true negatives, and 20 pre-VF or true positive signals, resulting in a **sensitivity of 100%** and a **specificity of 100%**.

C. Detection results

The time between the detection and the actual VF onset is crucial to test the effectiveness of the algorithm. It is also an indicator of the method's performance as it is desirable to detect an imminent VF with enough anticipation time as to allow some kind of preventive action. This time interval was different for each pre-VF patient (Table III), with and average of 312 seconds. This value represents a wide time margin as to take medical preventive actions.

In five subjects the detection occurred less than 15 seconds before onset, which means the detection was caused by the immediately prior tachycardia episode, a short interval present in many VF episodes. The intention of our detection method is to distinguish an indicator prior to this tachycardia, which was not met for these subjects.

D. Statistical Analysis

The difference between the ΔAVNN% and T_{AVNN}, and the ΔSDNN% and T_{SDNN} were calculated. A Student's t-test was done. Both variables were compared between the normal subjects and the pre-VF signals, showing $p < 0.001$ significance (Table IV).

It should be noted that the t-test assumes that the variables have a normal distribution. This assumption allows a first evaluation of the significance. However, this does not ensure a high fidelity but it is useful as a first approach.

TABLE III
TIME INTERVALS BETWEEN DETECTION AND VF ONSET FOR PRE-VF SUBJECTS.

Patient N°	$\Delta t_{detection-onset}$ **[s]**
1	111.28
2	458.51
3	216.15
4	4.60
5	4.85
6	679.67
7	733.94
8	676.73
9	553.02
10	9.00
11	4.22
12	43.16
13	1015.80
14	6.32
15	17.62
16	140.80
17	478.34
18	499.60
19	535.33
20	51.50

TABLE IV
MEAN, VARIANCE AND P-VALUES OBTAINED FROM THE STUDENT'S T-TEST.

	ΔAVNN% - T_{AVNN}		**ΔSDNN% - T_{SDNN}**	
	Normal	**VF**	**Normal**	**VF**
Mean	-0.359	0.566	< 0.001	0.006
Variance	0.013	0.365	< 0.001	< 0.001
***p*-value**	$p < 0.001$		$p < 0.001$	

IV. DISCUSSION

The goal of the designed algorithm is to find a combination of T_{SDNN} and T_{AVNN} whose performance is independent of database and therefore can be applied to any RR signal for VF detection. The databases which were available for this work were used to determine optimal thresholds ("learning phase"), and these thresholds showed an excellent performance for the same databases, but should be tested in new databases to verify that their performance is database-independent ("operative phase"). Otherwise, the 100% sensitivity and 100% specificity obtained are likely to be a result of overfitting.

The method that was developed is computationally very efficient due to the simplicity of the algorithm. As only few instructions are performed, it is suitable for implementation in MCUs in a real-time basis. Its low computational cost would allow its application in monitoring ECG devices as well as in implantable pacemakers.

The optimal time interval between the detection and VF onset depends on the desired application. In the case of an implantable pacemaker, a short prediction time is enough, as the charging time of the capacitor is usually a few milliseconds. However, if the detection occurs minutes before the onset, it could provide an additional warning of possible imminent VF, in an attempt to prevent the VF from occuring at all instead of preparing for defibrillating it.

In the case of a monitoring ECG system used in intensive care, a detection which triggers an alarm more than five minutes before onset becomes significantly useful, as it allows medical personnel to either prevent the VF or prepare an external defibrillator for discharge. It is important to realize that if this method could achieve a 100% specificity, the

significance of this detection becomes extremely valuable. The high specificity that our method has shown so far, makes it suitable for this goal.

Existing methods for the detection of imminent VF are based on detecting the tachycardia that usually precedes the onset. It should be clarified that our method would not be a substitute of this type of detection, but it serves as a complementary action. In the case of VF preceded by tachycardia, it would be useful as an extra warning flag, using the following detection of tachycardia as confirmation. However, in the case of spontaneous VF with a really short or absent preceding tachycardia, this method stands out as an even more valuable tool.

A limitation of this work is that it only uses one database for pre-VF. Therefore, the ΔSDNN% peaks might be characteristic of this database and not of pre-VF signals in general, being caused by the device's acquisition methods or its signal pre-proccesing.

It is necessary to test the method's performance in a greater number of VF onsets, in order to increase the statistical significance of its sensitivity. However, it is difficult to generate databases of RR signals preceding a VF episode, as this episode is completely undesirable. The only data available is obtained from advanced implantable pacemakers which are able to register and save this information, and with patient consent to make this information public. Obtaining a great N of testing signals is the greatest difficulty when developing VF detection methods. Nevertheless, with the promising results obtained so far, this method shows great advantage when compared to standard algorithms which are very robust. Its simplicity and the great time interval of anticipation it offers in detection, make it a promising tool for addressing imminent VF episodes with real-time implementation.

V. Conclusions and future work

This work presented a novel and simple algorithm for the detection of VF onsets. This effective indicator can be implemented in real time in a variety of medical devices with ECG modules. The method is based on mean and standard deviation of HRV. Preliminary results in 65 RR signals suggest that the proposed methodology is a powerful tool to detect imminent VF with 100% sensitivity and 100% specificity.

Perspective for future work include a deep evaluation of the proposed methodology, and generating and obtaining new databases to test the designed method and ensure a thorough testing of the algorithm. It is also of interest to find the probability distribution of the difference between the ΔAVNN% and ΔSDNN% and their respective thresholds as to generate an accurate model.

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