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Sequential Algorithm for the Detection of the Shockable Rhythms in Electrocardiogram

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Abstract— **We suggest a sequential algorithm for the detection of the ventricular fibrillation (VF) and ventricular tachycardia (VT) of a rate above 180 bpm, so called shockable rhythms. The built-in algorithm for ECG analysis embedded in the portable bio-signal sensing module is aimed to discriminate between shockable and non-shockable rhythms and its accuracy is analyzed. An algorithm for VF/VT detection is proposed to analyze every 1 s ECG episode using the past 8 s episodes. The method is tested with 844,587 ECG episodes from the widely accepted databases. A sensitivity of 86.8 % and a specificity of 99.4 % were obtained and compared with the previous results.**

I. INTRODUCTION

Ventricular fibrillation (VF) and ventricular tachycardia (VT) of a rate above 180 bpm are classified as dangerous cardiac disturbances, which may lead to death or unrecoverable aftereffect if no defibrillation shock is applied within a few minutes. Critical cardiac incidents occur most often outside hospitals, therefore automatic external defibrillators (AED) were introduced to enhance the survival rate, whose purpose is to recognize and treat VF and VT above 180 bpm in the absence of qualified medical doctors to diagnose the electrocardiogram (ECG) [1]. Similarly, it is also desirable for the portable bio-signal sensing module to detect so-called shockable rhythms as defined above [2] as well as to measure the heart rate for the everyday healthcare monitoring. Since the successful termination of VF and VT requires fast response and application of high-energy shocks in the hearts region, it is of great importance that the built-in algorithm for shockable rhythm detection is required to be highly accurate. Therefore the automated diagnosis using these external devices must match or at least be comparable to the accuracy of cardiology specialists in the case of VF/VT detection. Fast, reliable and accurate detection of shockable rhythm from a single-lead external ECG is a difficult task. Various methods have been proposed to classify the ECG rhythms including the VF and the VT. Recently, an improved version of the TCI algorithm called the threshold crossing sample count (TCSC) method [3] was reported to give quite accurate classification between VF and nonVF episodes. The amplitude distribution analysis (ADA) algorithm [4] was also proposed to detect the shockable rhythms correctly using relatively simple counting parameters. A mean absolute value (MAV) with empirical mode decomposition (EMD) method [5] was recently proposed giving quite accurate detection results of both shockable rhythms, VT and VF signals. However, some of these methods are computationally demanding or still difficult to implement in real-time operating devices, for example, AE D. Aiming at a simple solution, easily embeddable in a simplified system such as the mobile bio-signal sensing module using the MSP430 microcontroller unit (MCU), therefore operating in real time, we developed a sequential algorithm for shockable rhythm detection based on digital filtering and amplitude distribution parameters.

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II. MATERIALS AND METHODS

A. ECG signals

In this paper we have used the MIT-BIH Arrhythmia Database (MITDB) [6], Creighton University Ventricular Tachyarrhythmia Database (CUDB) [7], MIT-BIH Malignant Ventricular Arrhythmia Database (VFDB) [8], and American Heart Association (AHADB) [9] to evaluate our algorithm. The MITDB contains 48 files, 2 channels per file, each channel 1805 seconds long. The CUDB contains 35 files, 1 channel per file, each channel 508 seconds long. The VFDB contains 22 files, 2 channels per file, each channel 2100 seconds long. The AHADB contains 155 files, 2 channels per file, each channel 2099 seconds long. In our analysis, we have chosen episodes of 8-s [10] long from the whole MIT-BIH arrhythmia, CU, and AHA databases. We have performed a continuous computation by taking the 8-s ECG data in steps of 1 s. Thus, the total number of 8-s episodes collected from the MITDB, CUDB, and AHADB are (1805-7)×48×2 = 172608, (508-7)×35 = 17535, and (2099-7)×155×2 = 648520 respectively. The VFDB includes ECG recordings of patients who have experienced sustained VT/VF, therefore some of VF and VT episodes from this database were chosen for the analysis [5]. By taking the ECG signal in steps of 1 s we have chosen 5924 episodes of VF and VT from this database. Therefore, the total number of episodes to test our algorithm is 172608 + 17535 + 648520 + 5924 = 844587.

B. Algorithm

All analysis and test procedures presented in this paper were performed with Visual C++. The applied signal preprocessing as used in [10-11] includes (i) the mean value subtraction from the signal for 8 s (ii) a high-pass filter with 1 Hz cut-off frequency to suppress low-frequency residual baseline drift; (iii) a second-order 30 Hz Butterworth low-pass filter to reduce high-frequency noise. To equally distribute the computational demand at every sampling step on MSP430, it is assumed that the ECG signal sequence obeys the Markov property, that is, each ECG sample is solely dependent on the previous ECG samples, and the mean value to be subtracted during the filtration process is replaced by the mean value for the past ECG samples before *i*-th second sample. L_e in our algorithm is defined as the averaging time interval of the past samples.

To determine the heart rate of an ECG signal, the only positive part of first derivative of the ECG signal at t second (y_t) is utilized and the other part is assigned to be zero. Then the moving average filter of order = $f_{sample}/10$ is applied to this signal (y_t) and the number of peaks per minute is counted as given below [5].

$$\text{Period} = \frac{60}{L_e} \sum_{|t_{j-1}-t_j| \geq f_{sample}/4,\, y_t^{Max} \geq \frac{1}{4}\mathrm{Max}(y_t^{Max})} n(y_{t_j}^{Max}) \qquad (1)$$

where t_j is the peak position, y_t^{Max} is the local maximum value among the ECG samples, f_{sample} is the sampling rate of the ECG data and the minimum peak width is given by $f_{sample}/4$.

After the period calculation necessary for the detection of the shockable VT, another second-order Butterworth band-pass filter with 3.2 Hz and 61 Hz windowing frequencies is applied for the remained decision procedures. Firstly, noise and asystole episodes are detected. Some criteria is applied in order to detect abnormal signal amplitudes and slopes, uncharacteristic for ECG signals. The amplitude threshold is chosen according to the dynamic range of the input amplifiers and analogue to digital converters (ADC) to detect extreme artifacts (for example ADC saturation). The maximum slew rate limit above which a signal is ignored as 'noise' was set at 400 μVms^{-1}. Signals with amplitudes below 150 μV are classified as 'asystole' and not analyzed [4]. According to AHA recommendations, shockable rhythms include VF signals with amplitude larger than 200 μV and rapid ventricular tachycardia with a rate larger than 180 bpm.

Three counting parameters as defined in [4], C_1^i, C_2^i, and C_3^i at *i*-th second are reformulated for the 1-s time interval and calculated from the absolute values of the digital-filter out ($|x_i|$) at *i*-th second. Each parameter represents the number of ECG signal samples with amplitude values within a given amplitude distribution range, counted for 1-s time interval at *i*-th second. The respective counting ranges are defined as follows:

$$\begin{aligned} C_1^i &= \frac{1}{N} \sum_{\frac{1}{2}\mathrm{Max}(|x_i|) \leq |x_i| \leq \mathrm{Max}(|x_i|)} n(|x_i|) \\ C_2^i &= \frac{1}{N} \sum_{\langle |x_i| \rangle \leq |x_i| \leq \mathrm{Max}(|x_i|)} n(|x_i|) \qquad (2) \\ C_3^i &= \frac{1}{N} \sum_{\langle |x_i| \rangle - MD \leq |x_i| \leq \langle |x_i| \rangle + MD} n(|x_i|), \end{aligned}$$

where $\mathrm{Max}(|x_i|)$, $\langle |x_i| \rangle$, and MD (mean deviation) are computed for every 1-s time interval and N is the total number of samples in L_e seconds. Then, the parameters are averaged for L_e-s time intervals as given by the formula (3) and compared with the several pre-defined criteria [4] rescaled for 1-s time interval.

$$\langle C_\alpha^i \rangle = \frac{1}{L_e} \sum_{k=1}^{L_e} C_\alpha^{i-L_e+k} \qquad (3)$$

In this algorithm L_e = 8 s is chosen and the decision rules applied in the algorithm are given as below:

- If $\langle C_1^i \rangle < 0.1$ and $\langle C_2^i \rangle > 0.38$ and $\langle C_1^i \rangle \cdot \langle C_2^i \rangle / \langle C_3^i \rangle < 0.084$ the rhythm is classified as non-shockable.
- If $0.1 \leq \langle C_1^i \rangle < 0.16$ and $\langle C_2^i \rangle < 0.24$ and $\langle C_1^i \rangle \cdot \langle C_2^i \rangle / \langle C_3^i \rangle < 0.084$ the rhythm is classified as non-shockable.
- If $\langle C_1^i \rangle \geq 0.1$ and $\langle C_2^i \rangle > 0.38$ the rhythm is classified as shockable.
- If $\langle C_2^i \rangle \geq 0.44$ the rhythm is classified as shockable.

To analyze the remained 'Not decided' rhythms from these decision rules, we compute the period parameter given by (1) and decide the ECG signal as shockable if the period of the ECG signal is greater than 180 bpm. As the decision of shockable or non-shockable VT is dependent on the heart rate or period of the episode, hence, we count the number of peaks implying the total number of QRS beats on 8-s ECG episodes. We have estimated the period of each 8-s ECG episode from all physionet DB's [3-6] with the intervals among the annotated beats and labeled as 'non-shockable', 'shockable', 'asystole' and 'noise'.

III. RESULTS

Typical ECG waveforms of normal sinus rhythm (NSR), VT, and VF are shown in Fig. 1. We calculate the values for the quality parameters of the sensitivity, the specificity, the positive predictivity (+P), and compare the accuracy of our algorithm with other algorithms investigated in [5] as shown in Table I. As we can see in Table I, the detection results of the shockable rhythms using our algorithm are overall in good agreement with the previous extensive MAV & EMD calculations [5]. Table II gives the performance results over the ECG DB's considered in this paper in order to compare the detection results among the respective DB's using our algorithm. AHADB is also tested with our algorithm giving similar results (the values in parentheses in Table I).

TABLE I. SENSITIVITY (SE.), SPECIFICITY (SP.), POSITIVE PREDICTIVITY (+P.), AND ACCURACY (AC.) IN PERCENT OF DIFFERENT SHOCKABLE RHYTHM DETECTION ALGORITHMS

	Se.	Sp.	+P.	Ac.
MAV & EMD[a]	91.1	99.4	90.7	99.2
ADA[a]	88.9	99.3	86.0	98.9
Our work	88.0[b] (86.7)[c]	99.2[b] (99.4)[c]	85.9[b] (85.2)[c]	98.6[b] (98.9)[c]

a. [5].

b. Calculations performed on MITDB, CUDB, and VFDB.

c. Calculations performed on MITDB, CUDB, VFDB, and AHADB.

TABLE II. SENSITIVITY (SE.), SPECIFICITY (SP.), POSITIVE PREDICTIVITY (+P.), AND ACCURACY (AC.) IN PERCENT OF DIFFERENT ECG DATABASES USING OUR DETECTION ALGORITHM

	MITDB	CUDB	VFDB[a]	AHADB	Overall
Se.	78.7	78.0	95.0	86.1	86.7
Sp.	99.8	91.3	N/A	99.4	99.4
+P.	45.9	72.0	100.0	84.9	85.2
Ac.	99.8	88.4	95.0	99.0	98.9

a. VT and VF episodes considered only [5].

As shown in Table II, we notice that the relative low +P on MITDB is partly due to the extremely small number of VT and VF samples in MITDB, however, does not affect the overall +P calculation results. It is also noted that in the case of VFDB we selected VT and VF episodes only as described above.

IV. DISCUSSION

At every ECG data acquisition using the mobile bio-signal sensing module with MCU, it is desirable that the number of computing cycles needed to execute the algorithm is equally distributed for the overall ECG sampling and the computing time at each ECG data is sufficiently short enough to be finished before the next data acquisition. In this respect, the signal preprocessing using the mean value subtraction method adopted in this paper quite reduces the computing time at every 1 s and it may be justified with the detection results shown in Table I and II. The original ADA algorithm [4] is designed to be applied on every 10-s time interval, which means that we should wait for 9 s at worst if the shockable rhythm occurs just after the previous detection step. In this paper the detection is performed at every 1 s.

In real applications of AEDs or emergency calls from the mobile bio-signal sensing module on patients, the specificity is more important than other quality parameters, since a patient without any shockable rhythm should not be defibrillated due to a detection error which might cause mortal cardiac arrest. Therefore any detection algorithm for the shockable rhythm should give very high specificity even if this may increase the number of false negative classifications. We obtained the specificity of 99.4 % over all ECG DB's, quite reasonable agreement with the extensive calculations [4-5]. In this paper, the +P is also considered important because the higher +P means that the more true positive decisions are made among all positive decisions. As shown in Table II, consistent results on different well-known databases have been obtained using our algorithm. For MITDB, CUDB, VFDB, and AHADB, the calculation results on quality parameters using our algorithm are overall in good agreement with the previous works [4], implying that several modifications for the sequential algorithms in order to be embedded in the MCU, are reasonable enough to reproduce the equivalent quality parameters with the previously proposed algorithms [4-5]. The quality parameters obtained from MAV & EMD method are slightly better than our results, however it is noted that EMD method is usually time consuming and not suitable for the fast diagnosis of the shockable rhythms.

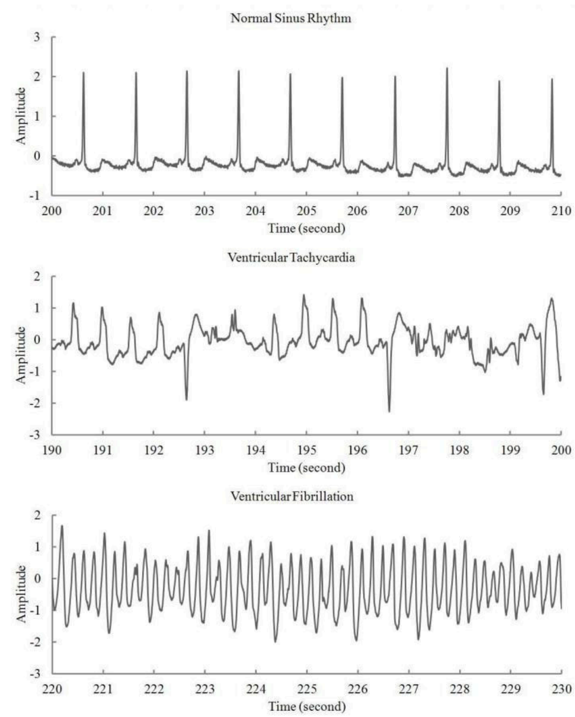

Figure 1. Typical NSR, VT, and VF waveforms

V. CONCLUSION

A simple sequential algorithm is proposed for the real-time detection of the shockable ECG rhythm. The built-in algorithm for ECG analysis embedded in the mobile bio-signal sensing module is aimed to discriminate between shockable and non-shockable rhythms and its accuracy is analyzed. Several modifications within our algorithm are suggested for the sequential execution at every ECG data acquisition and every 1-s decision of the ECG rhythm. Further modifications to separate the VF from the shockable rhythms are in progress.

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