On the eficiency of some signal descriptors to identify normal or abnormal cardiac rhythms

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Abstract - **This work presents a new study on characterization of EEG signal descriptors with possibility of use in mobile devices for prevention of heart attack. Various techniques are compared in order to design a system for identification of normal or abnormal windows in a continuous scanning acquisition. As result the potentialities of the considered signal descriptors on the identification of normal or abnormal cardiac rhythms are discussed.**

Keywords **- Electrocardiogram (ECG); Fast Fourier Transform (FFT); Wavelets; Signal Processing; Ventricular fibrillation.**

I. INTRODUCTION

Cardiovascular diseases are the leading cause of death worldwide [1]. Heart attack, heart failure, abnormal heart rhythms (arrhythmias), and diseases as: coronary artery, heart muscle, congenital and heart valve are the main cardiovascular affections. Arrhythmias are very frequent, and pathologic arrhythmias are related to disorders of excite-conductor system of heart. There are many types of arrhythmias, but ventricular arrhythmias as ventricular tachycardia (VT) and ventricular fibrillation (VF) leads to sudden death if not detected and treated in time [2]. Therefore, early detection of VT and VF is crucial for the success of the defibrillation therapy.

Normal ECG, as in Fig.1 and 2-top, are characterized by 60 to 100 beats per minutes and normal P wave, PR interval, ST interval, QRS complex, and QT interval [3]. Such intervals are known also as isoelectric intervals [4], and the heart rhythm as Normal Sinus Rhythm (NSR). Ventricular tachycardia (VT) (Fig. 2-center) is a rapid heart rhythm with more than 100 beats per minute, with at least three irregular heartbeats in a row starting in the lower part of the heart (ventricles) [5]. The PR and ST intervals are missing in VT episodes and QT intervals are very short due increment of heart beats rate [6]. VT is a potentially threatening arrhythmia because it may lead to ventricular fibrillation, non systoles (or asystole, also known as flatline, is a state of no electrical activity from the heart and therefore no blood flow) and sudden death. Isoelectric intervals are missing in ventricular fibrillation (VF) (Fig. 2-bottom) which is an emergency that must be treated immediately to save a person's life [5]. If this arrhythmia continues for more than a few seconds, it will likely degenerate further into systole [3].

Figure 1. Normal waves and intervals in ECG.

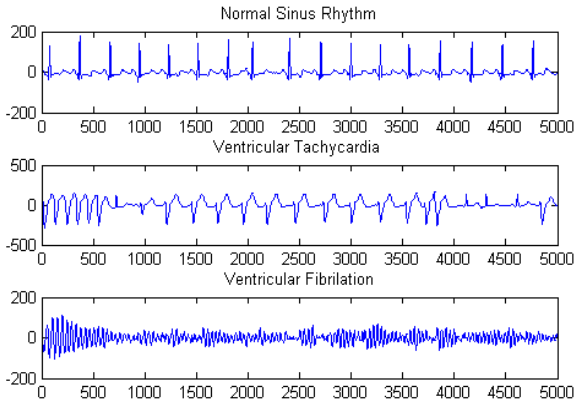


Figure 2. Different ECGs from MIT-BIH.

This paper aims to analyze a number of features in order to differentiate normal (NSR) and abnormal (VT and VF) heart rhythm transitions from ECGs. They can be used in future works to VF detection and discrimination between VF and VT. In next section we analyze briefly related works. Then signal descriptors are presented in Section III, and their results discussed in Section IV. Finally, conclusions and recommendations can be found in comments.

II. RELATED WORKS

Automatic VF detection is a difficult problem because it can be appears as chaotic or non-chaotic signal [7], and VT is a quasi-periodic signal sometimes misinterpreted as VF. A wide variety of methods to VF detection and discrimination between VF and VT have been reported [2, 4-14]. The majority of these methods are based on the study of signal descriptors, or features, using ECG signal processing. These descriptors quantify the amount of information present in ECG signal on time, frequency or time-frequency domain [4-6, 8]. Two features in time domain and 25 features from Pseudo Wigner-Ville distribution in time-frequency domain were studied in [8]. The notion of short-time multifractality have been used to develop a novel approach for arrhythmia detection, assuming that cardiac rhythms are characterized by short-time generalized dimensions (STGDs) and used a fuzzy Kohonen neural network to classify different types of arrhythmias [9]. Misplacements are applied to signal based on time-delay signal approach for extract different features [10-12] and also analyzed by Empirical Mode Decomposition [5, 13, 14].

III. SIMPLE SIGNAL DESCRIPTORS

A digital ECG is a time-discrete set of electrical values (samples) time-ordered registered at same time interval Δt from a continuous ECG signal. The time interval Δt is the sampling interval. The quantity of samples by unit of time (generally one second) is the sampling frequency (Fs). The sampling frequency must be greater than twice the maximum frequency to be sampled [15]. Thus, a digital ECG can be seeing as a time series of samples. An ECG window X from one derivation is a subsequence $X=\{x_1, x_2, \ldots, x_N\}$ of N samples from a digital ECG. Statistically an ECG window can be quantitatively seen as a random variable.

A. Signal Complexity and Signal Mobility

These descriptors use the first derivative of signal samples: $d_1=x_i-x_{i-1}$, and the second derivative: $g_1=d_i-d_{i-1}$, to define the S_0, S_1, and S_2, as in (1-left), (1-center) and (1-right) [16]:

$$S_0 = \sqrt{\frac{\sum_{i=1}^{N} x_i^2}{N}}, \quad S_1 = \sqrt{\frac{\sum_{i=1}^{N} d_i^2}{N-1}}, \quad S_2 = \sqrt{\frac{\sum_{i=1}^{N} g_i^2}{N-2}} \tag{1}$$

Signal Complexity (SComp) (2) quantifies the signal energy [16]. Signal Mobility (SMob) (3) is known as first-order normalized variation:

$$SComp = (S_2^2/S_1^2 \; - \; S_1^2/S_0^2 \;)^{1/2}, \quad SMob = S_2/S_1 \tag{2)(3}$$

B. Entropy and Correlation

Entropy (E) (4) is a measure associated with the amount of order, disorder, or randomness in a thermodynamic system [17]. Signal with high randomness presents high values of entropy.

$$E(X) = -\sum_{i=1}^{N} p(x_i) log_2\big(p(x_i)\big) \tag{4}$$

where $p(x_i)$ is the probability of sample x_i in the window X.

Correlation (C) is a statistical measure to quantify the strength and direction of a linear relationship of random variables: being near 1 it means strong correlation between two variables and same direction; a 0 indicates that the variables are not correlates, and -1 means that variables are strongly correlates but in the opposite direction (i.e. variation of a variable causes opposite variation the other variable with same magnitude). Here, the Pearson's correlation coefficient (5) is used to correlate two ECG windows X and Y [18].

$$C(X,Y) = \frac{N\sum x_i y_i - \sum x_i y_i}{\sqrt{N\sum x_i^2 - (\sum x_i)^2}\sqrt{N\sum y_i^2 - (\sum y_i)^2}} \tag{5}$$

C. Fractal dimension

Fractal dimension (FD) is a ratio to compare how the detail of a pattern changes concerning the scale it is measured. Higuchi method is an approximation to determinate FD for one-dimensional signal [19]. This value can be estimated as the tangent of the angle of the best fitted line for a set of points $(x;y)$ (6).

$$(x;y) = \left(log_2\left(\frac{1}{k}\right); log_2\big(L(k)\big)\right) \tag{6}$$

This line described by $(x;y)$ can be estimated by Least Squares adjustment. Sub-sequences at different resolutions k are sampled from X (an ECG window). Considering m=1,2,3…k, the average length $L_m(k)$ of each sub-sequence at resolution k is determined by (7).

$$L_m(k) = \frac{\sum_{i=1}^{\left\lfloor \frac{(n-m)}{k} \right\rfloor} |x(m+ik) - x(m+(i-1)k)|(n-1)}{\left\lfloor \frac{N-m}{k} \right\rfloor k} \tag{7}$$

where $m = 1, \ldots, k$. The space filled of an ECG with NSR is less than to a problematic ECG and, consequently, its FD is smaller [19].

D. Root Mean Square and Short Time Average Energy

The Short Time Average Energy (STAE) (8) quantifies the signal energy (high values contribute much more to it). The root mean square (RMS) (9) is a measure of the energy contained in the signal that is independent of the sampled.

$$STE(X) = \sum_i {x_i}^2, \quad RMS(X) = \left(\frac{1}{N}\sum_i {x_i}^2\right)^{1/2} \tag{8)(9}$$

The RMS over time of a periodic function is equal to the RMS of one period of this function. The RMS value of a signal can be approximated by taking the RMS of a sequence of equally spaced samples. Random signals as VF have more energy than periodic signals as RSN. See that equation (9) can be derived from (8).

E. Zero Crossing Rate

Zero Crossing Rate (ZCR) (10) is a measure to determinate the number of times the signal changes from positive to negative values and vice versa. VF and VT episodes are characterized by higher rate of zero-crossing than other arrhythmias due the high randomness.

$$ZCR(X) = \frac{1}{N-1}\sum_{i=1}^{N-1} |sign(x_i) - sign(x_{i-1})| \tag{10}$$

Where $sign(x_i) = 1$ if and only if $x_i \geq 0$, and $sign(x_i) = 0$ if and only if $x_i < 0$.

F. Discrete cosine transform

Discrete cosine transform (DCT) allows a hierarchy in the value of information. The first coefficient is called DC and other coefficients are the AC. DC coefficient concentrates the majority part of signal energy or information [23].

$$\bar{X}[k] = a[k]\sum_{n=0}^{N-1} X[n]\cos\left(\frac{(2n+1)\pi k}{2N}\right) \tag{11}$$

The Inverse DCT (12) (IDCT) is used to obtain the original signal values from all DC and AC coefficients [23],

$$X[n] = \sum_{k=0}^{N-1} a[k]\bar{X}[k]\cos\left(\frac{(2n+1)\pi k}{2N}\right) \tag{12}$$

where $a[k] = (1/N)^{1/2}$ to $k=0$ and $a[k] = (2/N)^{1/2}$ to $k=1,\ldots,N-1$, in both equations (11, 12). Here, two descriptors from DCT component are used to characterize ECG signals: the energy of the signal (13) and the maximum absolute value of the DCT components, MaxCV (14):

$$E(X) = \sum_k (X[k])^2 \tag{13}$$

$$\text{MaxCV(X)} = max_{k=1,\ldots,N-1}\{|\bar{X}[k]|\} \tag{14}$$

G. Fourier transform

Discrete Fourier transforms (DFT) is used to transform signals from time domain (analysis) to frequency domain (15), and vice versa (synthesis) (16).

$$X[k] = \sum_{n=0}^{N-1} x[n] e^{\frac{-j2pnk}{N}}, \qquad x[n] = \frac{1}{N} \sum_{k=0}^{N-1} X[k] e^{\frac{j2pnk}{N}} \qquad (15)(16)$$

for *k=0, 1, 2, ..., N-1* and *n=0, 1, 2, ..., N-1*, respectively. Here, the sum of absolute values of the complex component obtained with Fast Fourier Transform algorithm is used as signal descriptor [23].

H. Wavelet transform

The Wavelet transform (17) can provides information about a signal in time and frequency together at once [20].

$$\Psi_{a,b}(t) = \frac{1}{\sqrt{a}} \Psi\left(\frac{t-b}{a}\right) \qquad (17)$$

where $a = 2^j, b = k2^j, (j,k)\, \epsilon\, Z^2$. Scale and shift are used in wavelet transform being associated with a use of a high-pass and low-pass filters bank, respectively [23]. Here the sum of the squares of detail coefficients from wavelet transform of an ECG window is used as signal descriptor. In the experimentations to be described in next section the Haar, Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal, and ReverseBiorthogonal mother wavelet functions are used.

IV. EXPERIMENTATIONS

Experimentations have used MatLab R2014a running in an Intel Core i7 computer and annotated ECG signals from PhysioBank repository of Physionet [21]. Randomly 905 episodes of VF, 392 of TV and 5502 of RSN were selected with 8 seconds of time-length from 3 databases [21]. Table 1 presents details of used databases. All episodes were taken from channel 1 of the selected records.

TABLE I. PHYSIOBANK DATABASES USED

Database	N. records	Channels	Freq. (Hz)	Total time [s]
MITDB	48	2	360	1805.555
CUDB	35	1	250	508.928
VFDB	22	2	250	2100

ECG signals are filtered as described in [22]. In order to evaluate the correlation it is necessary to take a time-delay of the window related to signal, for this 3 time delays are used (Correlation60, Correlation80 and Correlation100 related to 1s, 3/4s and 3/5s delays, respectively). They have been considered according to what must be a normal cardiac frequency, i.e. from 60 to 100 beats/minutes. Fig. 3 shows samples of these, where the blue lines represent the original signal and in red there are the signals with the delays. From examining the signals in such organizations, it is possible to see that major correlation for a specific NSR-window appears when a delay of 3/4s for a frequency (Fc) of 80 beat per minutes is considered. Although the graphs in Fig. 3 represent only the here related delays, we have experimented a number of then. To construct the combination of signal to compute correlations, the sampling frequency of a signal is added with a delay of the same signal. For instance, if the signal has Fs = 360 Hz, or 360 samples per second, and if we named A and B initial and final samples of the original window (blue), then, for a heart rate is Fc=60 bpm (that is, 360 samples per second) it is possible to see that a delayed signal with 360 samples (delay = 1s) would be correlated (red line) with the original signal and consequently 1s would be the period of the sign. Moreover, as in general the averaged Fc are close to 80 bpm, i.e. a beat every 3/4s, then in a second we would have 270 samples instead of 360, this was observed in the computed windows, because the correlation values was higher for such a delay (270 samples). In the case of Fc=100 bpm (delay=3/5s, that is 214 samples) the correlation was lower. Thereafter, for Figure 3, A and B are the initial and final samples of the original window (in blue, fixed in the three graphs), the indices of the windows of the used delay are: (1) for Fc=60 d=1s represented by A-360 B-360, (2) for Fc=80 d=3/4s represented by A-270 B-270, and (3) for Fc=100 d=3/5s correspondent to A-214 B-214.

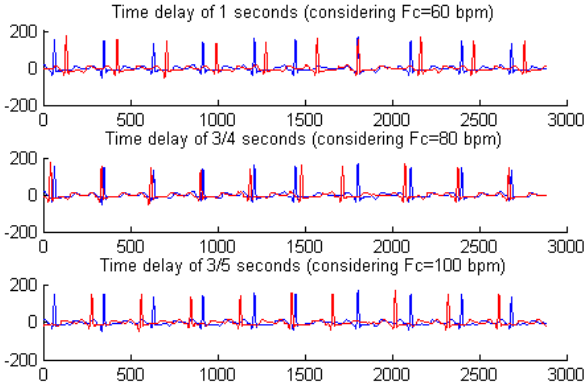


Figure 3. Original and delayed ECG with 1s, 3/4s and 3/5s of time-delays.

Table II shows the mean values obtained by descriptor for each group of arrhythmias of interest. Although, a variety of sub type of the mothers wavelet are here used (Haar, Daubechies-2, Daubechies-4, Daubechies-8, Daubechies-12, Daubechies-20, Daubechies-32, Coiflets-1, Coiflets-3, Coiflets-5, Symlets-2, Symlets-10, Symlets-20, Discrete Meyer, Biorthogonal-1.1, Biorthogonal-2.2, Biorthogonal-3.1, Bi-orthogonal-3.9, Rever-se-Biorthogonal-1.1, ReverseBiortho-gonal-2.2, Reverse-Bior-thogonal-3.1 and ReverseBiortho-gonal-3.9) in table II, for space restrictions, only the most relevant of these descriptors are registered.

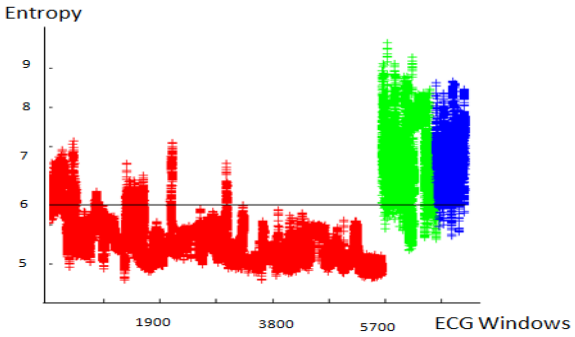
The results show that using these descriptors it is possible to separate NSR episodes from VT and VF episodes, but do not VT from VF, because of the overlap and similarity between VT and VF cardiac rhythms. For example, for the feature Entropy the values of VT and VF are very closed (Fig. 4). To understand this, the entropy values (in y-axis) from each ECG window (in x-axis) are displayed in Fig. 4 as points. To construct this graphs, firstly we organized them showing the entropy of each of the 5502 episodes of NSR (red points), then we display to each of the 905 episodes of VF (green points), and finally we represent the 392 episodes of VT (blue points). The majority of Entropy values from NSR windows are bellow 6 and well separated of those from VF and VT, as can be seen in Fig. 4.

V. CONCLUSIONS

In order to achieve the conclusion of this work we have made a big number of experiments with the 3 used databases. Of course they are very dependent of these database and differences can be found when other databases will be used. Even though, most of the other works in the literature put focus on only one features, we have considered a big number of them for the ECG records employed an the three DBs. Finally, about

our results, it is possible to say: (1) that those descriptors based on frequency domain achieved higher values in VT than in VF, because many of the VF windows are characterized by low intensity values; and (2) the best time delay to be used for correlation is related with 100 beat per minute cardiac frequency.

We recommend: (1) make experiments with all ECG signals in MIT-BIH databases, (2) use the same filtering process over all ECG episodes, (3) use the studied descriptors and supervised classification algorithms to classify the heart rhythm in real time for detection of ventricular arrhythmias.



a. Entropy for NSR (red), VF (green) and VT (blue) versus grouped windows.

TABLE II. MEAN AND STANDARD DEVIATION BY FEATURE

Feature	RSN	VT	VF
Signal Complexity	0.171	0.1480	0.106
Signal Mobility	9.687	9.454	8.087
Entropy	6.163	7.191	7.959
Correlation60	0.155	-0.263	0.046
Correlation80	-0.155	-0.330	0.029
Correlation100	0.192	0.461	0.026
Root Mean Square	63.111	69.212	72.848
S-Time Avg. Ener.	9591397.455	13002136.949	11769349.720
Zero Cross. Rate	0.021	0.131	0.179
Energy FFT	1301955.405	1426406.822	1307718.205
Energy DCT	9591397.455	13002136.949	11769349.7204
WT-haar	25593.715	54331.789	49110.395
WT-db2	1018.722	1723.727	1148.823
WT-db8	14.290779	26.168546	19.235361
WT-db20	4.022392	16.097732	5.471690
WTsym10	10.130987	14.141198	13.699269
WT bior 3.1	10.301357	12.676889	8.752017

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