# 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 the normal or abnormal window in a continuous scanning acquisition. As result the potentialities and efficiency of the considered signal descriptors on the identification of normal or abnormal cardiac rhythms are discussed.**

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

## I. INTRODUCTION

Cardiovascular diseases are the leading cause of death worldwide [1]. Heart attack, heart failure, abnormal heart rhythms (arrhythmias), coronary artery, heart muscle, congenital and heart valve diseases 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 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.

ECG normals, 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 middle) 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) [7]. 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 asystoles also known as flatline, it 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 [7]. If this arrhythmia continues for more than a few seconds, it will likely degenerate further into systole [3, 7].


Figure 1. Normals waves and intervals in ECG.

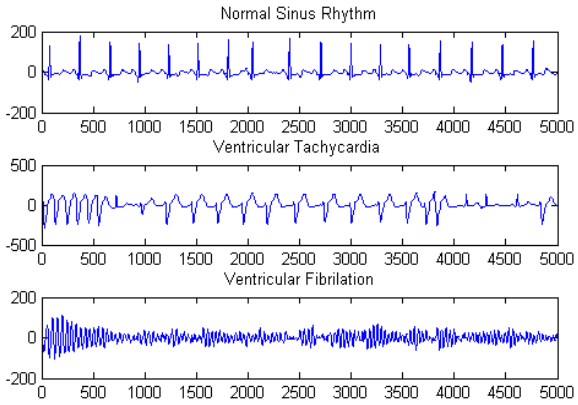


Figure 2. ECG with diferents heart rhythms from MIT-BIH.

The objective of this paper is to analyze a number of features in order to differentiate normal (NSR) and abnormal (VT and VF) heart rhythm transitions from ECG. These features will be used in furthers works to VF detection and discrimination between VF and VT. In next section we analyzed 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 Section V.

## II. REVIEWING SOME RELATED WORKS

Two features in time domain and 25 features from Pseudo Wigner-Ville distribution in time-frequency domain are studied [9]. Automatic VF detection is a difficult problem because it can be appears as chaotic or non-chaotic signal [8], 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 [4-7]. 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 [13, 14, 23].

## III. SIMPLES SIGNALS DESCRIPTORS

A digital ECG is a time-discrete set of electrical values (samples) time-ordered takes at same time interval $\Delta t$ from a continuous ECG signal. The time interval $\Delta t$ 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 [16]. 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 seen as a quantitative randomness variable.

### A. Signal Complexity and Signal Mobility

These descriptors use the first derivative of signal samples $x_i$: $d_1=x_i-x_{i-1}$, and the second derivative: $g_1=d_i-d_{i-1}$, to define the $S_o$, $S_1$, and $S_2$, as in (1 left), (1 center) and (1 right) [17]:

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

Signal Complexity (*SComp)* (2) quantifies the signal energy [16]. Signal Mobility (*SMob*) (3) relates the raw signal respect to its first derivative and 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.

$$E(X) = -\sum_i p(x_i)\, log_2(p(x_i)) \tag{4}$$

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].

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

### 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* of 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).

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

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 sign.

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

The RMS over time of a periodic function is equal to the RMS of one period of the function. The RMS value of a signal can be approximated by taking the RMS of a sequence of equally spaced samples. Randomness signal 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 quantity of sign-changes, i.e. the rate at which the signal changes from positive to negative 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 $x_i > 0$, and $sign(x_i) = 0$ if and only if $x_i < 0$.

### F. Discrete cosine transform

Discrete cosine transform (DCT) permits concentrate most of the information in a few transformed coefficients. The first coefficient is called DC and other coefficients are the AC. DC coefficient concentrates the majority part of signal energy and 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 $k=2,\ldots,N-1$, 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 values, 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 at same time [22].

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

where $a = 2^j, b = k2^j, (j,k)\, \epsilon\, Z^2$ [23]. 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 of next section the Haar, Daubechies, Coiflets, Symlets, Discrete Meyer, Biorthogonal, and ReverseBiorthogonal mother wavelet functions are used.

## IV. Experimentations and Conclusions

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 from 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, the blue lines represent the original signal and in red there are the signals with the delays, where it is possible to see that major correlation for a specific NSR-window appear 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, if a heart rate is Fc=60 bpm (that is, 360 samples per second) then 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=100bpm (delay=3/5s, that is 214 samples) the correlation was lower. Then, 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 for Fc=60 d=1s are A-360 B-360, for Fc=80 d=3/4sa are A-270 B-270, and for Fc=100 d=3/5s are A-214 B-214.

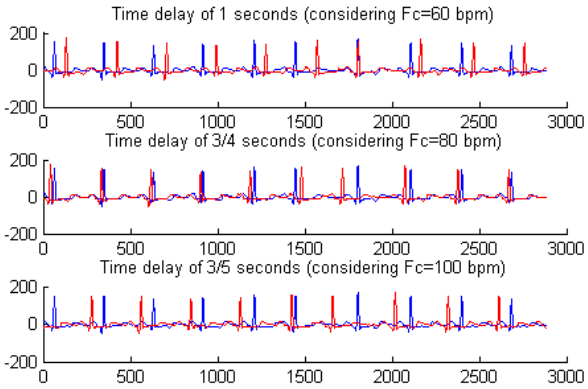


Figure 3. Original and delayed ECG with 1s, 3/4s and 3/5s of time-delays.

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 type 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. Entropy values indicate that VF and VT episodes are those.

To understand this, the entropy value (in y-axis) from each ECG window (in x-axis) are displayed in Fig. 4 as points. Firstly, are showed the entropy values of each of the 5502 episodes of NSR (red points), at same form to each of the 905 episodes of VF (green points), and finally to each of 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 when the window position is considered as well, as can be seen in Fig. 4.

In order to achieve the conclusion of this work we have done a big number of experiment with the 3 used database. Of course they are very dependent of this and differences can be found when other databases will be used. However, most of the other works in the literature put focus on only one features we

have considered a big number of them for 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 analyze is related with 100 beat per minute cardiac frequency. Finally, as these results can be influenced by the filtering process various filter process will be used soon.

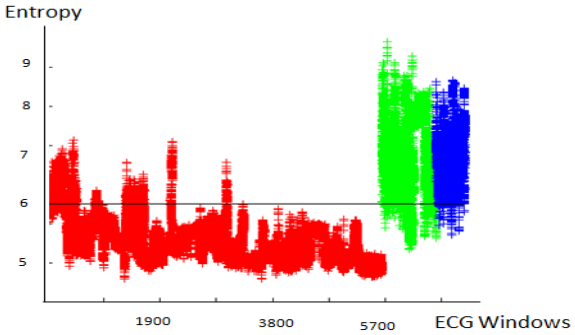


Figure 4. Entropy for NSR (red), VF (green) and VT (blue) versus grouped windows.

TABLE II. MEAN AND STANDARD DEVIATION BY FEATURE

| Feature | RSN | VT | VF |
|---|---|---|---|
| Signal Complexity | 0.171 ± 0.035 | 0.1480 ± 0.005 | 0.106±0.016 |
| Signal Mobility | 9.687 ± 3.225 | 9.454 ± 0.049 | 8.087 ± 1.674 |
| Entropy | 6.163 ± 0.934 | 7.191 ± 0.073 | 7.959 ± 0.353 |
| Correlation60 | 0.155 ± 0.335 | -0.263 ± 0.017 | 0.046 ± 0.287 |
| Correlation80 | -0.155 ± 0.234 | -0.330 ± 0.008 | 0.029 ± 0.351 |
| Correlation100 | 0.192 ± 0.284 | 0.461 ± 0.016 | 0.026 ± 0.365 |
| Root Mean Square | 63.111 ± 26.705 | 69.212 ± 3.623 | 72.848 ± 24.068 |
| S-Time Avg. Ener. | 9591397.455 | 13002136.949 | 11769349.720 |
| Zero Cross. Rate | 0.021 ± 0.004 | 0.131 ± 0.0017 | 0.179 ± 0.008 |
| 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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