ECG Feature Extraction Based on Joint Application of Teager Energy Operator and Level-Crossing Sampling

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***Abstract*—Continuous health monitoring provides a promising way for early detection of complications development in patients with chronic conditions and plays significant role in forward-looking applications and services related to fitness, well-being, chronic diseases treatment and independent living for elderly. A number of arrhythmia detection algorithms are being developed within a CardiaCare project that is aimed at continuous monitoring of heart function in real-time and analyzing electrocardiograms on a smartphone. Arrhythmia detection algorithms are heavily rely on features extracted from electrocardiogram recordings, in particular, on reliable detection of QRS complexes. In this paper, we present fast and reliable algorithm based on joint application of Teager energy operator and level crossing sampling resulted in high detection performance indicators.**

I. Introduction

According to World Health Organization so-called cardiovascular diseases (CVDs) are the leading cause of death globally: more people die annually from CVDs than from any other cause. It is typical for Commonwealth of Independent States (CIS) as well.

TABLE I. CVD contribution to mortality in CIS

Georgia	67
Ukraine	64
Azerbaijan	60
Russia	57
Moldova	56
Belorussia	53
Kazakhstan	50
Armenia	50
Kyrgyzstan	49
Tajikistan	39

Majority cardiovascular diseases can be prevented by addressing behavioural risk factors such as tobacco use, unhealthy diet and obesity, physical inactivity and harmful use of alcohol. People with cardiovascular disease or who are at high cardiovascular risk need early detection and management using counselling and medicines, as appropriate.

Within the CardiaCare project the efforts are concentrated on the development of the continuous monitoring system aimed timely detection of rhythm abnormalities. Despite the fact that the arrhythmias are harmless in general, they can pose serious threat of complications against chronic diseases such as hypertension or diabetes. Therefore, continuous heart rhythm monitoring provides the possibility to detect the deterioration of heart function and even to save the life.

The system operates as it is shown in Fig. 1. Raw cardiogram data are received by smartphone app and passed to the analysis core.

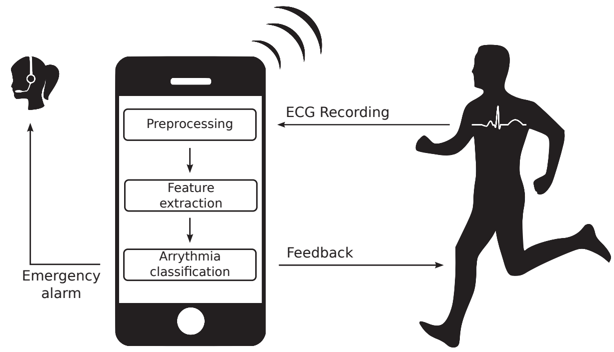


Fig. 1. Continuous monitoring system operation

Detection of cardiac abnormalities relies on electrical activity of the heart that can be registered and visualised with a plot that is known as cardiogram. Each feature of the cardiogram is related to activity of specific part of the heart from atrial contraction to ventricular relaxation. Normal sinus rhythm of the cardic cycle consists of five typical waves: P, Q, R, S and T.

Most important in analysis is the highest point of the R wave, so-called R peak. Successful identification of R peaks allows to split the signal into segments on which other features can be estimated. Examples of different rhythm anomalies that are aimed to be catched in CardiaCare project are shown below.

In normal sinus rhythm you see the lengths of RR interval in 60-100 beats per minute (bpm). This rhythm is shown in Fig. 2 Sinus tachycardia, characterized with frequent beats (more than 100 bpm), is illustrated by Fig. 3. If sinus bradycardia occurs the heart rate is below 60 bpm. Bradycardia recording is shown in Fig. 4.

In Fig. 5, 6, 7 there are arrhytmias that require more detailed analysis but R peaks play a vital role in localization of cardiac cycles.

It is obvious that in this scenario precise but complicated algorithms cannot be used since heavy computations can drain the battery of mobile device in minutes.

Fig. 2. Normal sinus rhythm

Fig. 3. Sinus tachycardia

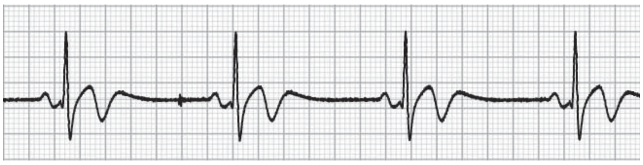


Fig. 4. Sinus bradycardia

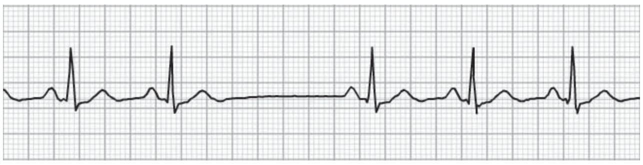


Fig. 5. Sinoatrial block

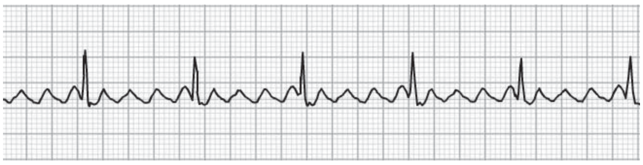


Fig. 6. Atrial flutter

Fig. 7. Wolff-Parkinson-White syndrome

One of the methods was proposed by Yamamoto and Yoshida in 2013 [1]. This approach based on Teager-Kaiser energy operator widely used in speech processing [2]. This operator defines energy of a signal produced by a simple harmonic oscillator. Due to less computational requirements this method is prominent for devices with restricted energy capabilities. In this work the one-pass algorithm based on Teager-Kaiser energy operator computation was constructed, tested against the real ECG recordings and implemented as a standalone library.

II. R Peak Detection Based on Teager-Kaiser Energy Operator

Let us briefly discuss the background of Teager-Kaiser Energy Operator (TKEO). Detailed explanation can be found in [2] and [3]. Consider an object with mass m suspended by a spring with a constant factor characteristic of the spring, or stiffness, k. If the mass is displaced from its equilibrium position, a restoring elastic force is exerted by the spring. This force which obeys Hooke's law and is given by

$$F = -kx \tag{1}$$

where x is the displacement from the equilibrium position. The following second order differential equation can be deduced by means of Newton's second law to describe the simple harmonic motion of considered object and is given as

$$F = \frac{d^2x}{dt^2} + \frac{k}{m}x = 0 \tag{2}$$

The solution to equation 2 is given by

$$x(t) = A\cos(\omega t + \phi) \tag{3}$$

where $x(t)$ is the position of the object at time t, A is the amplitude, ω is the frequency, and ϕ is the initial phase. The total energy of the object is given as the sum of kinetic energy of the object and the potential energy of the spring, given by

$$E = \frac{1}{2}kx^2 + \frac{1}{2}m\dot{x}^2 \tag{4}$$

By substituting $x(t) = A\cos(\omega t + \phi)$, we get the following expression for the energy:

$$E = \frac{1}{2}mA^2\omega^2 \tag{5}$$

Now we consider the continuous-time form of Teager energy operator defined to be

$$\Psi_c[x(t)] = (\dot{x}(t))^2 - x(t)\ddot{x}(t) \tag{6}$$

Substituting $x(t) = A\cos(\omega t + \phi)$, we obtain

$$\Psi_c[x(t)] = A^2\omega^2 \tag{7}$$

Thus, the operator defined by 6 is the amplitude and frequency product squared. But from 5 the total energy is proportional to the amplitude and frequency product squared.

In order to get the discrete-time form of the operator, consider the digital signal x_n given by

$$x_n = A\cos(\Omega n + \phi) \tag{8}$$

where Ω is the digital frequency $\Omega = 2\pi f/F_s$. Here f is analog frequency and F_s is the sampling frequency. By means of trigonometric identities we obtain

$$x_{n-1}x_{n+1} = A^2\cos^2(\Omega + \phi) - A^2\sin^2(\Omega) \tag{9}$$

Substituting $A^2\cos^2(\Omega + \phi)$ with x_n^2 we get

$$A^2\sin^2(\Omega) = x_n^2 - x_{n-1}x_{n+1} \tag{10}$$

Restricting Ω to be positive and less than $\pi/4$ and approximating the $sin(\Omega)$ with Ω we get the unique solution with approximation error less than 11%. Hence, the discrete-time form of the Teager energy operator is defined by

$$\Psi_d[x_n] = x_n^2 - x_{n-1}x_{n+1} \tag{11}$$

Since R peaks have high frequency component and usually high amplitude, this approach is useful to enhance these peaks and suppress the other features.

The method proposed in [1] involves three base steps.

1) Estimation of the instantaneous energy of a signal

$$\Psi_d[x_n] = x_n^2 - x_{n-1}x_{n+1}$$

2) Emphasis of the R peaks

$$y_n = \Psi_d[x_n]^3$$

3) Choosing parameters N, α and β and computing the adaptive threshold

$$z_n = \alpha \frac{1}{N+1} \sum_{k=-N}^{N} y_k + \beta \sigma_y$$

Parameters α and β depend on a signal and N should be chosen from one to doubled length of RR interval.

The algorithm can be implemented in one-pass in obvious way if we modify the sum in threshold for every sample.

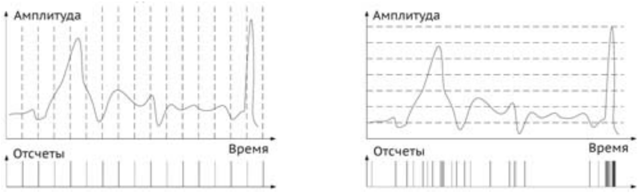
For the appropriate thresholding at least one R peak should happen during the window size. And for better results one R peak should happen exactly.

III. Level crossing

The wearable and implanted sensor devices possessing means of wireless data transfer are in center of attention of vendors of medical and consumer electronics now. In such systems the key value is acquired by signal quality, volume of transmitted data and consuming of energy. The traditional analog-to-digital converters, as a rule, use uniform sampling of signals, continuously generating counting and consuming energy irrespective of character of the read-out biomedical signals. For reduction of volume of transmitted data and increase in energy efficiency on the side of sensors different techniques of non-uniform sampling are used. One of such approaches is the method of intersection levels [24], [25].

When sampling the continuous signal the method of intersection of levels implies that the initial analog value (tension, current intensity, temperature, etc.) which value changes over time, is displayed in the discrete set of values by the following method: the range of possible values of an analog signal breaks into a set of the intervals restricted to the lines of level corresponding to values of levels of quantization; the value on an output of the transformer appears at the time of intersection by a signal of the line of level (fig. 8). Use of a method of intersection of levels is justified by smaller energy consumption and smaller level of intrinsic noises of the transformer.

In spite of the fact that initially the method of a perecheniye of levels was used for sampling of analog signals [26], [27], [28], [29], there were recently operations in which this method is applied to a digital signal for the purpose of detection of the structural elements which are characterized by high concentration of intersections of the levels, in other words, surrounding peak values of segments.



a) b)

Fig. 8. Comparison of uniform sampling and sampling on level

We will consider a signal of $x(t)$. We will select a set of lines of level $\{L_1, \ldots, L_m\}$ (let for simplicity level spacing identical and equally to q), then, having applied the described method, we will receive the discrete sequence of intersections $\{x_1, \ldots, x_n\}$ and the appropriate sequence of timepoints $\{t_1, \ldots, t_n\}$ (see fig. 9). We will designate $interval[t_{i-1}, t_i]$ for dt_i.

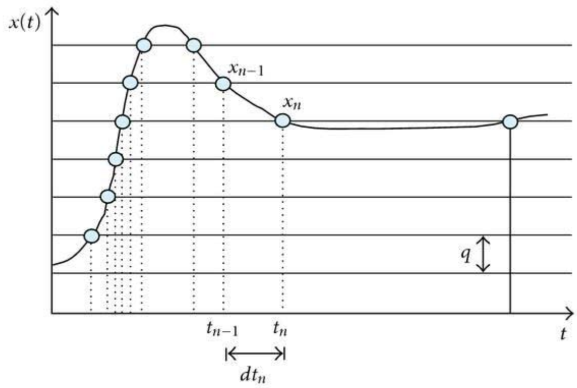


Fig. 9. Creation of the sequence of intervals between crossings of levels

Depending on activity of a signal the frequency of crossings will be various as crossings will arise only when there is an essential change in value of a signal, that is irregularly. The quicker the initial signal changes, the crossings are located more closely to each other, the time intervals between them are shorter. Therefore, the short time intervals surrounding rather large number of crossings can be surveyed as indicators of peaks and complexes of peaks. Obviously, the method will be effective when processing of the signals discharged the wave-like. Treat similar signals also an ECG signals.

IV. Algorithm of definition of a QRS complex

The traditional system of definition of a QRS complex includes a set of the components necessary for receiving, strengthening, processing of a signal and decrease in his zashumlennost. Use of the systems based on a method of crossing of levels and processing of unevenly had data [21], [22], [23] is one of new approaches to detection of QRS complexes.

As it has been shown in the previous section, short time intervals between crossings of levels correspond to signal peaks (fig. 10). This property can be used for detection of a QRS complex or, at least, localization R peaks.

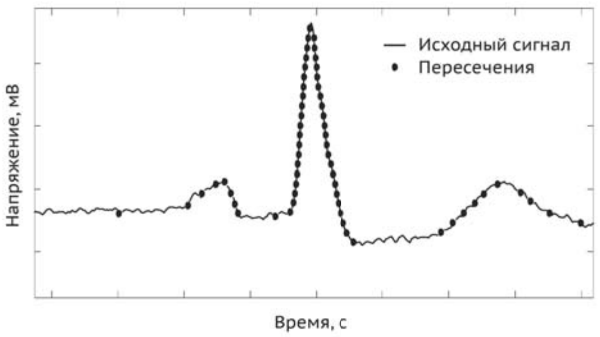


Fig. 10. Use of a method of crossing of levels to an ECG signal

We will consider the transformer providing permission in M bits, then we have $2^M - 1$ levels of quantization. The input signal always is between two lines of level, for N values of a low significant bit (LSB) which is defined as

$$LSB = \frac{2A}{2^M},$$

where A defines the range of input amplitude (tension). When the input signal crosses the upper or lower line, we remember counting and we shift pair of levels on one value of LSB. Then new levels of quantization are compared to an input signal again. Use of $N > 1$ smooths an input signal as though preliminary filtering as in this case after each change of the direction in an input signal from growth to falling and vice versa $N - 1$ intersection in the same direction is passed was executed, and noise with an amplitude it is less, than N values of LSB, are filtered.

We will look for R peaks among the moments of intersections of t_k. We will define the sliding window in W serial intersections (taking into account passed in case of $N > 1$).

$$D(t_k) = \sum_{i=t_k-\left[\frac{W}{2}\right]}^{t_k+\left[\frac{W}{2}\right]-N+l} dt_i.$$

The notation of $[x]$ in a formula designates the greatest integral number which is less or equally x, at the same time is entered the correction of l:

$$l = \begin{cases} 0 & W, \\ 1 & W. \end{cases}$$

If the size of $D(t_k) of$ doesn't surpass in advance chosen threshold value of T, then the moment of crossing of t_k is considered peak.

As the signal of an ECG is influenced by such factors as reduction of muscles and respiration, the final drawing can change therefore to reduce sensitivity of an algorithm to threshold value of T, it is adaptive adapts during processing of a signal as follows. We will enter two additional estimates: SP—the changing D size assessment for a signal of R-waves, and NP—the changing D size assessment for the collateral peaks which aren't R-peaks. Then, if the found peak is R-peak, then

$$SP = SP - [c1 \times (SP - D)],$$

otherwise

$$NP = NP - [c1 \times (NP - D)],$$

and for each found peak value the threshold of T is updated according to

$$T = SP + [c2 \times (NP - SP)].$$

Values of constants of $c1$ and $c2$ are chosen peer 0.25 for simplicity of integer realization with use of bit operations.

V. Realization of an algorithm

For realization of an algorithm the program in language C ++, providing calculation of the moments of crossing, the potential moments of peaks and the moments of the beginning of a QRS complex is written. For definition of the moment of the beginning of a QRS complex, the return viewing of the sequence of intervals of dt_i from the moment of potential peak is used until size doesn't exceed the doubled average value in a chain.

At the same time for focusing on an algorithm, but not features of realization, in the program arithmetics with a floating point is used, the organization of calculations with use of integer arithmetics and bit operations isn't considered.

Following [23], as entrance values of M, W, N are chosen, respectively, 7, 7 and 4.

The program reads out from standard input the size of range of tension (number in a format with the fixed point, the representing tension expressed in millivolts), then the sequence of couples of values (each couple from a new line) representing line representation of a temporary mark (which in the program isn't interpreted in any way) and, through a gap, tension size in a format with the fixed point. As the output data on a standard conclusion the program prints the sequence of the temporary marks corresponding to the moments of the beginning of the found QRS complexes.

VI. Possible improvements of an algorithm

We will notice that when detecting a QRS complex emergence of various sources of hum, such as muscular contractions, shift of the ECG basic line due to respiration, the hums arising at contact to an electrode, especially in case of wearable devices faces a problem. Other components of signals, such as P and T waves can also break detection process. Besides, the main morphological features of a QRS complex vary from the patient to the patient. Thus, almost all algorithms of QRS of detection use several types of filtration for suppression of undesirable parts of a signal. At realization of such filters the complexity of calculations and power consumption is enlarged. By means of the surveyed method it is possible to reject the most part of undesirable hums and signals with an amplitude less, than a preset value. Thanks to this property, for detection of a QRS complex the simple algorithm without use of any auxiliary schemes or calculations can be applied to additional filtration.

To avoid false detection of QRS because of the fast high T-waves characteristic of an ECG of some patients, the adaptive limiting temporary zone in which any found QRS complexes which are too close to previous are rejected is established. For measurement of RR of intervals, it is possible to use the local timer, or the interval of time can be calculated by summation of values of dt_i. This part of an algorithm can be realized by comparison of a time interval between the current counting and the previous R-peak with a threshold of the limiting zone which is chosen PB peer to a half of an average RR interval. The value of PB is established initially in 1 second (a normal rhythm) and every time when the R-peak is taped, its value is adaptive is updated, with use of the following equation:

$$PB = PB - [c3 \times (PB - \Delta T)]$$

The value of $c3$ is chosen 0.125 to simplify realization. Coefficients are chosen so that all operations of multiplication can be realized by means of rejection of bits.

VII. Experiments

In recent years achievements in the field of apparatus technologies made possible to collect the larger databases consisting of a multichannel ECG. The most extensive and freely available collection of the ECGs wave forms can be found in the databank PhysioNet [30] representing a set of databases. This set of databases contains hundreds of an ECG received from the patients having various heart diseases and also examples of an ECG of healthy people lasting from 30 minutes about one days and more. These records were annotated by experts-clinicians and, in certain cases, are checked by automatic algorithms. For check of efficiency of algorithms of definition of QRS and arrhythmias the database of arrhythmias of MIT-BIH (MIT-BIH Arrhythmia Database) of PhysioNet bank is used. The database of arrhythmias MIT-BIH contains 48 half-hour excerpts from two-channel out-patient records ECG with marks from 100 to 124 and from 200 to 234, received from 47 patients investigated in laboratory of arrhythmias of BIH during the period from 1975 to 1979. 23 records ECG are chosen in a random way, other 25 records represent less widespread, but clinically significant arrhythmias. Records are digitized with a frequency of 360 Hz on the canal with the resolution of 11 bits in the range of 10 mV. Each record was annotated by two or more cardiologists independently of each other. This base of arrhythmias will be used for check of efficiency of the surveyed method of detection of QRS - complexes, based on crossing of levels.

VIII. Conclusion

During this work we have implemented the novel algorithm designed to detect R peaks on an electrocardiogram and we have developed the system to verify the detectors on a set of signals from MIT-BIH database. Average sensitivity of the algorithm approximately equals to 95 percents that is quite good. The worst case is the 91 percents achieved on the notoriously 207 signal that is reported to be too hard for well-known precise methods as well.

Acknowledgment

This research is financially supported by the Ministry of Education and Science of Russia within project no. 2.5124.2017 of the basic part of state research assignment for 2017–2019. The reported study was funded by RFBR according to research project # 16-07-01289.

TABLE II. QRS Detection Performance

TP	FN	FP	$Precision$	$Recall$	F
2273	1	0	0.99956	1	0.99978
1857	15	12	0.991987	0.993579	0.992783
2098	25	89	0.988224	0.959305	0.97355
2078	8	5	0.996165	0.9976	0.996882
2111	124	125	0.944519	0.944097	0.944308
2272	152	336	0.937294	0.871166	0.903021
1326	156	703	0.894737	0.653524	0.75534
1877	106	261	0.946546	0.877923	0.910944
1369	127	444	0.915107	0.755102	0.82744
2453	89	77	0.964988	0.969565	0.967271
1681	16	435	0.990572	0.794423	0.88172
2536	23	3	0.991012	0.998818	0.9949
1791	9	10	0.995	0.994448	0.994724
1108	69	747	0.941376	0.597305	0.730871
1952	3	1	0.998465	0.999488	0.998976
2318	86	79	0.964226	0.967042	0.965632
1532	10	3	0.993515	0.998046	0.995775
2157	264	120	0.890954	0.947299	0.918263
1401	485	592	0.742842	0.70296	0.722351
1448	3	415	0.997932	0.777241	0.873868
2475	4	2	0.998386	0.999193	0.998789
1516	22	1	0.985696	0.999341	0.992471
1598	9	20	0.9944	0.987639	0.991008
2388	216	217	0.917051	0.916699	0.916875
1886	32	43	0.983316	0.977709	0.980504
2118	8	11	0.996237	0.994833	0.995535
2420	269	573	0.899963	0.808553	0.851813
2622	2	29	0.999238	0.989061	0.994123
1665	122	545	0.931729	0.753394	0.833125
2093	878	851	0.704477	0.710938	0.707692
2965	110	41	0.964228	0.986361	0.975169
2454	75	157	0.970344	0.93987	0.954864
2336	123	412	0.94998	0.850073	0.897254
1675	2239	1574	0.427951	0.515543	0.467681
2148	37	113	0.983066	0.950022	0.966262
3246	40	114	0.987827	0.966071	0.976828
1983	65	225	0.968262	0.898098	0.931861
2101	71	92	0.967311	0.958048	0.962658
2037	4	10	0.99804	0.995115	0.996575
2350	18	75	0.992399	0.969072	0.980597
2353	43	114	0.982053	0.95379	0.967715
2551	34	53	0.986847	0.979647	0.983234
1797	213	270	0.89403	0.869376	0.881531
2229	43	27	0.981074	0.988032	0.984541
1570	3	1	0.998093	0.999363	0.998728
1778	14	9	0.992188	0.994964	0.993574
2313	398	763	0.853191	0.751951	0.799378
2746	18	6	0.993488	0.99782	0.995649

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