# IMPLEMENTATION OF AN EFFICIENT R-PEAK DETECTION ALGORITHM ON A 16 BIT MICROPROCESSOR FOR A SUBCUTANEOUSLY IMPLANTABLE HEART-RISK-MONITOR

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**Abstract: The objective was the development of an efficient R-Peak detection algorithm that can be installed in an implantable risk-monitor for permanent recording of cardiac risk parameters. Parameters of cardiac risk stratification, e.g. heart rate variability, are extracted from the cardiotachogram. A prerequisite for the correctness of the risk parameters is the valid R-Peak detection that also yields reliable results when applied to a non-standard recording of the heavily disturbed electrocardiogram. Several detector algorithms have been examined with real data from a standard ECG database (MIT-BIH Arrhythmia Database, MIT-BIH Noise Stress Test Database). Superposition of the ECG signal with a noise signal results in a distinct signal to noise ratio (SNR) that simulates disturbing influences on the signal quality. The SNR is determined by using a method for the estimation of the power of the ECG signal as well as the noise signal. The algorithm which provides the best prerequisites for implementation, e.g. high numeric efficiency and detection reliability, was selected. Modifications of the original algorithm have to be considered as the constraints for the implementation. This modified algorithm could be realized without worsening the detection reliability. The adapted algorithm was implemented on a 16 bit microprocessor in C/C++ and the numeric differences to the extensive algorithm were assessed.**

**Key words: R-Peak detection algorithm, cardiac risk monitoring, tele-monitoring, microprocessor**

## Introduction

Diseases of the cardiovascular system are considered as the dominating cause of death in the western industry states. In the year 2003 in Austria 45.2 percent of all deaths were caused by such diseases. Patients with coronary diseases, cardiomyopathies or ventricular tachy-arrhythmia have a high risk for sudden cardiac death. Conventional risk parameters, like high cholesterol level, arterial hypertension or diabetes mellitus, allow to identify groups with increased risk but cannot be used for continuous risk monitoring. The challenge, however, is to monitor permanently and continuously the individual risk of patients who belong to a high risk group. The ECG is a signal that may reveal the development of a dangerous situation, e.g. by evaluation of heart rate variability including the impact of the autonomous nervous system and of the heart rate turbulence caused by extrasystoles.

For patients with higher risk it is necessary that their vital functions are monitored continuously and permanently. This approach gives them some safety and increases their quality of life. That objective can be reached by using an implantable tele-monitoring device which sends messages to the doctor in case of emergency.

Further requirements:

- small and easy to handle,
- no necessity of mechanical heart contact,
- possibility of ECG data recording,
- possibility of configuration and maintenance e.g. with an external controlling device through the skin,
- possibility of the implementation of several risk-stratification- algorithms,
- long battery life time (10 years and more).

Some of the above mentioned requirements are already realized in cardiac pacemakers. Therefore it is feasible to define such a tele-monitoring device as a derivate of a pacemaker. Only functions that are necessary are retained whereas others like ability to stimulate are discarded. The electrodes are integrated in the case of the device. The device itself can be implanted subcutaneously in the chest area near the heart to achieve a good signal quality.

Detecting of the cardiac status and prediction of a high risk condition is only possible if the used device can record longer ECG episodes of e.g. 1 hour after a critical cardiac event like bursts of extrasystoles. Therefore an appropriate memory must be integrated in this device (e.g. 2.8 MB at 16 bit quantization and 370 Hz sampling frequency for one episode). The biggest advantage of such a device is that the patient can stay at home while the recorded data as well as alarms can be transmitted to the doctor. The ECG recorded with such a system shows distinct differences in the signal mor-


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phology from the well-known surface ECG and a poorer signal to noise ratio.

Due to the fact that the concerned patients want to increase their quality of life, permanent risk monitoring requires the employment of an implantable tele-monitoring system. With regard to technical limitations, e.g. processing capacity of the microprocessor, battery power, and volume of the device, tailored procedures must be considered for signal processing. The objective of this study was to develop a tailored method for R-Peak detection.

## Materials and Methods

Different published detection algorithms have been evaluated with regard to robustness against noise from e.g. the electrode-tissue interface, muscle artefacts or baseline wander combined with high sensitivity and selectivity for the detection of regular R-Peaks. The methodological approaches for these algorithms are based on signal overlay, amplitude and first derivation, only first derivation, first and second derivation, digital filter and Hilbert transform. Table 1 shows an overview of the tested algorithms. They all have been implemented in MatLab™, in order to evaluate their performance.

Table 1: Overview of the considered algorithms

| Algorithm | Author | Category |
|---|---|---|
| AF1 | Moriet-Mahoudeaux [4] | Amplitude and first derivation |
| AF2 | Fraden, Neumann [4] | Amplitude and first derivation |
| AF3 | Gustafson [4] | Amplitude and first derivation |
| FD1 | Menard [4] | First derivation |
| FD2 | Holsinger [4] | First derivation |
| FS1 | Balda [4] | First and second derivation |
| FS2 | Ahlstrom, Tompkins [4] | First and second derivation |
| DF1 | Englese, Zeelenberg [4] | Digital filter |
| DF2 | Okada [4] | Digital filter |
| Zero Crossing Counts, ZeroC | Köhler, Henning, Orgelmeister [1] | Signal overlay |
| Hilbert transformation | Benitez, Gaydecki, Zaidi, Fitzpatrick [5] | Hilbert transformation |

In order to simulate the influences of noise on the ECG signal, three different noise types are used: baseline wander, electrode motion and muscle artefacts. Each noise type is combined with the ECG signal with different SNR (Signal to Noise Ratio): -6 dB, 0 dB, 6 dB, 12 dB, 18 dB and 24 dB. This approach reveals the weaknesses or strengths of each algorithm. In order to reach a certain SNR it is necessary to calculate the power of both the ECG signal and the noise signal.

Common methods for estimating the power, e.g. based on the mean-square amplitude, cannot be used to estimate the power of an ECG signal, because they are proportional to the heart rate. For the application here an estimation is needed that takes the algorithm's detecting ability into account. For that reason the power of the ECG signal is defined by QRS-complexes. The power of the noise signal is defined as the frequency weighted noise-power.

In order to estimate the power of the ECG signal only the first 300 QRS-complexes of a ECG record are used. Each QRS-complex is then approximated by a sinusoidal function which is a very good estimation for the power of the QRS-complex. The power of the noise signal is estimated using the first 300 seconds of the signal. Both parameters exclude some ECG records from the database, because they do not have 300 normal QRS-complexes, respectively [2]. This method of estimating the power of the ECG signal provides correct SNR values only during QRS-complexes. Due to the fact that the algorithm's detection ability is related to the QRS-complex this estimation of the power is adequately precise.

The database on which the tests are performed is the MIT-BIH Arrhythmia Database that contains 48 ECG records of half-hour length. The three noise records are available from MIT-BIH Noise Stress Test Database. Both used resources are recognised as standard databases. As proposed in [3] this study can be classified as reliable, because the study is based on standard signal archives.

In order to compare the algorithms the sensitivity (*Se*) and positive predictive value (*P+*) are calculated. These two values can be combined into one parameter, the Diagnostic Quality Factor (*DQF*) which is defined as the geometric mean of *Se* and *P+*. The mean value of the *DQF* is called the mean *DQF* (*mDQF*). *mDQF* is defined as the arithmetical mean of a set of *DQF* values.

From the selection of algorithms shown in Table 1, R-Peak detectors that apply amplitude thresholds have been discarded in a first step since it is not guaranteed that the processed signals are stable with regard to the amplitude. In the following section the remaining algorithms DF1, DF2, "Zero Crossing Counts" and "Hilbert transformation" are shortly described and the parameter-optimisation is explained.

The algorithms DF1 and DF2 are based on digital filters. With QRS detection algorithms that are based on digital filters disturbances can be suppressed efficiently also at the time when R-Peaks are detected. This is an advantage in relation to the other algorithms mentioned. However a higher cost of computation time is caused when using the digital filters [4].

The characteristics of the "Zero Crossing Counts" algorithm is that the ECG is overlaid with a alternating low-power signal that is derived from the ECG record. The basic frequency of this low-power signal is half of the sampling frequency of the ECG signal. It generates zero crossings in the band-pass filtered ECG record, which are counted in a defined time window. If a R-

Peak arises, then the rate of zero crossings is low. A time window is determined, in which the R-Peak in the original ECG record is looked for. Important is to employ a band-pass-filter with linear phase, because otherwise a correct temporal localisation of the R-Peak is not possible. The filtered ECG signal contains only the QRS-complex. The amplitude of the P- and T-wave and the mean-amplitude are attenuated so that the detection ability is not influenced.

The characteristics of the "Hilbert transformation" algorithm is that it exhibits a zero crossover, if and when in a signal (in this case the first derivative of the electrocardiogram signal) a turning point occurs. For R-Peak detection the first derivative of the ECG signal and the Hilbert transformed first derivative of the ECG signal are used [5].

All algorithms without the Hilbert-transformation based algorithm have one or more free parameters that render possible to adjust the detection ability of the algorithm. In case of one free parameter, this parameter is varied within plausible values and tested on each ECG sequence of the database. The result is a vector for each ECG sequence which represents the *DQF* in dependence of the free parameter. First the vectors are optimised to calculate a signal-specific free parameter. Then the optimum of the mean of the vectors is determined so that a database global parameter value is obtained.

For the "Zero Crossings Counts" algorithm which has three free parameters that can affect the detection ability, one parameter is kept constant and the other two are varied within a feasible range. In the next iteration the next free parameter is kept constant and the other two are varied. This procedure is repeated until the *DQF* is optimised. As mentioned before in this case also a parameter triple is selected which fits best to each ECG sequence and to the whole database.

The above mentioned noise test is performed with the signal-specific parameters in order to reveal some ECG signal features that are difficult to detect. With the use of the signal-specific parameter the results are slightly better than with the database global parameter. Exception is the Hilbert transformation based algorithm which has no free parameter. For the selection of one algorithm in order to be implemented on a microprocessor three quality criteria are essential: noise robustness, detection ability and computational efficiency.

## Results

In this section the four remaining algorithms are compared taking into account the above defined quality criteria. The best performing detection algorithm is selected in order to be implemented on a microprocessor.

Figure 1 shows the result of the noise test for the "Zero Crossing Counts" algorithm with the overlay of electrode motion at selected SNRs. The *mDQF* decreases with decreasing SNR. For an ideal algorithm all curves would have zero slope for a SNR that goes against negative infinity and *mDQF* would be 100 %. The mean value curve doesn't lay in the middle of the maximum and minimum curve. This can be explained by the fact that the database has only a limited number of signals (in this case 48). Each extreme ECG sequence with e.g. very poor signal quality strongly distorts the overall result.

Because all algorithms are tested on the same database with the same SNR conditions it is possible to compare the results. Furthermore the noise test reveals the advantages and shortcomings of the algorithms, e.g. difficulties with a certain noise type.

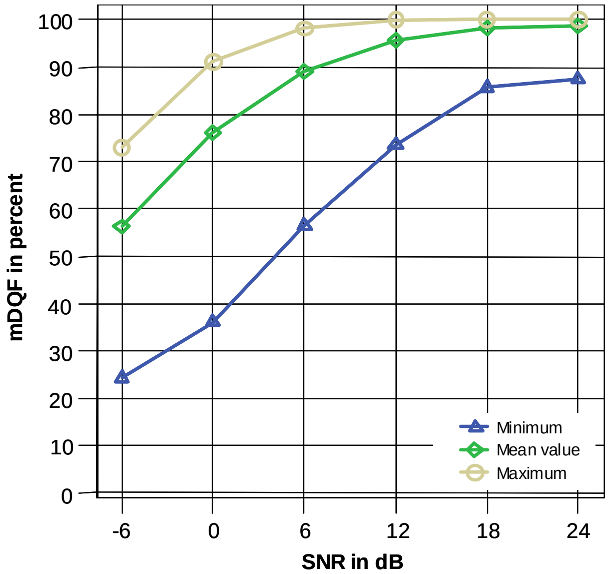


Figure 1: Detection ability of the "Zero Crossing Counts" algorithm (noise type: electrode motion, ECG records from MIT-BIH Arrhythmia Database)

The following tables (Table 2 to 4) show the quantitative results of the performed noise test. This test is performed on less signals than available in the MIT-BIH Arrhythmia Database and always using the signal-specific parameter. As shown in Table 3 and 4 the Hilbert transformation based algorithm performs best. The slope of the *mDQF* vector is smaller than the slope of the other vectors. Only during noise overlay of electrode motion the "Zero Crossing Counts" algorithm is better than the other algorithms.

Table 2: Detection ability of the algorithms with noise overlay of electrode motion and signal-specific parameters

| SNR in dB | *mDQF* | | | |
|---|---|---|---|---|
| | DF1 | DF2 | Hilbert | ZeroC |
| -6 | 48,02 | 35,73 | 36,12 | 57,4 |
| 0 | 58,34 | 56,89 | 67,44 | 76,7 |
| 6 | 70,61 | 82,31 | 90,99 | 90,32 |
| 12 | 84,43 | 95,52 | 96,51 | 95,98 |
| 18 | 95,52 | 98,43 | 97,11 | 98,48 |
| 24 | 97,8 | 98,67 | 97,2 | 99,1 |

Table 3: Detection ability of the algorithms with noise overlay of muscle artefacts and signal-specific parameters

| SNR in dB | *mDQF* | | | |
|---|---|---|---|---|
| | DF1 | DF2 | Hilbert | ZeroC |
| -6 | 51,75 | 19,24 | 60,43 | 49,71 |
| 0 | 60,6 | 48,45 | 76,8 | 64,39 |
| 6 | 73,98 | 77,78 | 91,54 | 81,07 |
| 12 | 91,08 | 93,67 | 96,58 | 91,02 |
| 18 | 97,57 | 98,25 | 97,15 | 96,68 |
| 24 | 98,09 | 98,69 | 97,22 | 98,52 |

Table 4: Detection ability of the algorithms with noise overlay of baseline wander and signal-specific parameters

| SNR in dB | *mDQF* | | | |
|---|---|---|---|---|
| | DF1 | DF2 | Hilbert | ZeroC |
| -6 | 80,82 | 82,77 | 93,56 | 86,85 |
| 0 | 93,29 | 94,29 | 96,58 | 94,47 |
| 6 | 97,35 | 97,61 | 97,15 | 97,78 |
| 12 | 98,05 | 97,98 | 97,24 | 98,96 |
| 18 | 98,1 | 98,75 | 97,42 | 99,13 |
| 24 | 98,14 | 98,75 | 97,74 | 99,19 |

In addition to the details of the noise robustness of the algorithms it is also necessary to evaluate the standard detection ability. Table 5 shows the results of the reached *DQF* and *mDQF* for the four algorithms for all signals of the MIT-BIH Arrhythmia Database without noise signals. Under this condition the Hilbert transformation based algorithm and the “Zero Crossing Counts” algorithm are superior to the digital filter based detectors. However, since they have nearly the same value for *mDQF* it is not possible to identify which algorithm performs better.

This leads to the last defined quality criteria, the computational efficiency, since the number of usable processor cycles between two consecutive R-Peaks on a microprocessor is limited. Digital filter based algorithms perform well although they require a high computational effort. They are not able to meet the requirements of computational efficiency.

The comparison of the computational effort for the Hilbert transformation based algorithm and the “Zero Crossing Counts” algorithm reveals that the “Zero Crossing Counts” algorithm needs less computational time due to the fact that the mathematical operations are much simpler (in contrast to the Hilbert transformation itself). In contrast to the algorithms that have been already discarded, the “Zero Crossing Counts” algorithm demands significantly more computational effort.

Table 5: *DQF* and *mDQF* of four selected algorithms with database global parameter

| **Signal Nr:** | ***DQF*** | | | |
|---|---|---|---|---|
| | **DF1** | **DF2** | **Hilbert** | **ZeroC** |
| 100 | 99,912 | 99,978 | 99,98 | 99,978 |
| 101 | 99,705 | 99,759 | 99,76 | 99,786 |
| 102 | 99,268 | 80,181 | 99,34 | 99,314 |
| 103 | 99,952 | 99,976 | 99,86 | 99,976 |
| 104 | 96,255 | 90,568 | 98,63 | 97,259 |
| 105 | 94,128 | 96,352 | 99,28 | 99,268 |
| 106 | 62,393 | 98,169 | 91,53 | 96,307 |
| 107 | 72,352 | 71,213 | 99,91 | 99,626 |
| 108 | 88,645 | 91,298 | 92,85 | 85,808 |
| 109 | 99,309 | 60,03 | 99,51 | 89,659 |
| 111 | 99,694 | 96,192 | 99,86 | 99,929 |
| 112 | 99,784 | 99,009 | 99,98 | 99,961 |
| 113 | 72,217 | 99,972 | 99,97 | 99,972 |
| 114 | 88,148 | 99,814 | 99,79 | 99,814 |
| 115 | 99,949 | 99,949 | 99,95 | 99,974 |
| 116 | 83,59 | 99,501 | 99,29 | 99,379 |
| 117 | 99,805 | 99,611 | 99,97 | 99,967 |
| 118 | 97,124 | 84,069 | 99,98 | 99,283 |
| 119 | 90,905 | 99,849 | 99,95 | 100 |
| 121 | 99,919 | 75,118 | 99,92 | 93,252 |
| 122 | 99,96 | 98,751 | 99,98 | 99,96 |
| 123 | 99,803 | 99,934 | 99,87 | 99,901 |
| 124 | 98,757 | 81,207 | 98,91 | 99,877 |
| 200 | 85,824 | 87,881 | 99,29 | 98,766 |
| 201 | 99,464 | 98,127 | 96,34 | 99,079 |
| 202 | 99,766 | 99,348 | 98,06 | 99,859 |
| 203 | 85,617 | 94,672 | 92,32 | 96,19 |
| 205 | 98,921 | 99,868 | 99,62 | 99,679 |
| 207 | 24,694 | 85,406 | 94,85 | 89,719 |
| 208 | 96,777 | 96,945 | 83,56 | 95,11 |
| 209 | 98,949 | 99,308 | 99,43 | 99,95 |
| 210 | 96,432 | 98,642 | 96,84 | 98,806 |
| 212 | 94,941 | 99,566 | 99,87 | 100 |
| 213 | 40,451 | 95,15 | 93,68 | 98,403 |
| 214 | 95,977 | 95,231 | 99,51 | 98,867 |
| 215 | 99,176 | 98,629 | 97,85 | 99,538 |
| 217 | 90,857 | 75,83 | 99,80 | 99,819 |
| 219 | 99,002 | 99,053 | 99,63 | 99,93 |
| 220 | 99,829 | 99,976 | 99,93 | 99,976 |
| 221 | 99,526 | 97,34 | 96,33 | 98,317 |
| 222 | 96,708 | 99,839 | 94,26 | 99,859 |
| 223 | 99,462 | 98,077 | 94,70 | 97,256 |
| 228 | 96,777 | 87,852 | 99,32 | 94,77 |
| 230 | 98,972 | 99,801 | 99,98 | 99,933 |
| 231 | 99,968 | 99,151 | 99,90 | 99,936 |
| 232 | 99,691 | 99,387 | 99,83 | 93,046 |
| 233 | 83,819 | 94,215 | 98,30 | 99,414 |
| 234 | 99,964 | 99,964 | 99,84 | 99,927 |
| ***mDQF*** | **92,15** | **94,16** | **98,15** | **98,23** |

The process of implementation of the "Zero Crossing Counts" algorithm has been realised in two steps. First of all the algorithm must be transformed to fixed point operations. On a microprocessor, in this case a derivative of the MC68HC12 family from Motorola, floating point operations should be avoided because they need approximately 70 times more processor cycles for the calculation than fixed point operations. The implementation has to be very efficient in order to use as few processor cycles as possible. Additionally it is a request that several different algorithms can be processed at the same time. So it is possible to extract a complete set of cardiac risk parameters.

The next step is to merge the fixed point implementation to the microprocessor simulation IDE (Integrated Development Environment). In this case the Metroworks Codewarrior IDE was used. The algorithm written in MatLab™ script code has to be translated to a C/C++ source code. During this translation the algorithm is split into logical sub-processes. The process of implementation ends up with fine tuning. This means that some mathematical operations are rearranged to reduce the necessary amount of processor cycles even more.

Finally the difference between the floating point (MatLab™ version) and the fixed point (microprocessor version) algorithms is evaluated. For this reason the modified C/C++ methods are again merged back into MatLab™. Each sub-process is compared to the floating point version with regard to amplitude behaviour and time factors. This evaluation showed that due to the simple mathematical operations of the "Zero Crossing Counts" algorithm, there is no severe difference in the temporal localisation of the R-Peak in the ECG signal. Only the time window in which the R-Peak is searched varies for 15 ms at the beginning and for 3 ms at the end. These time differences are short in the comparison to the total period of the QRS-complex and don't affect the detection result.

The estimation of the used processor cycles in the microprocessor simulation environment showed that this implementation needs approximately 968 cycles/sample. This number varies slightly because some operations depend on the number of detectable signal-features.

## Discussion

The three quality criteria (noise robustness, detection ability and computational efficiency) showed, that the "Zero Crossing Counts" algorithm is the best algorithm available in this study. The average noise robustness combined with a very good standard detection ability and low computational effort makes clear that the "Zero Crossing Counts" algorithm is also appropriate for the implementation on a 16 bit microprocessor.

The validation of the fixed point version of the algorithm against the floating point version of the algorithm showed no remarkable difference in the detection ability and the temporal localisation of the R-Peak. The reached precision is appropriate although the number of processor cycles is reduced significantly.

The free parameters of the algorithm have been optimised on the MIT-BIH Arrhythmia Database only. Future works have to consider the implementation of a sophisticated parameter optimisation algorithm that enables to adjust the detection ability within some seconds. This parameter adjustment would be appropriate for the individual ECG of each patient.

Finally the cardiotachogram that is calculated by the detection algorithm can be used for further processing of cardiac risk parameters, e.g. calculation of the Heart Rate Variability.

## Conclusions

The "Zero Crossing Counts" algorithm on the microprocessor platform can be used for an implantable heart-risk-monitor. The algorithm has been optimised with regard to efficiency, precision and microprocessor work load.

All the above mentioned requirements, e.g. detection reliability and low computational effort, add into the total concept of an implantable risk monitor. This risk monitor, which extracts meaningful risk parameters of the cardiac risk stratification in real time, is capable to augment the quality of life of the patients.

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