MODEL-BASED EVALUATION OF DIFFERENT QRS DETECTION ALGORITHMS FOR USE IN MOBILE SYSTEMS

G. v. Wagner[1], W.Stork[1,2], K. Müller-Glaser[1,2]

[1]Medizinische Informationstechnik, FZI Forschungszentrum Informatik, Karlsruhe, Germany
[2]Institut für Technik der Informationsverarbeitung, Universität Karlsruhe (TH), Germany
vwagner@fzi.de

SUMMARY: Monitoring high-risk patients requires high-quality online ECG classification in mobile systems. For safety reasons, any alarms have to be re-confirmed on a stationary system.
The first classification step for both systems is reliable QRS detection, but different approaches have to be taken on each of them due to the significant difference in available computational power.
This article presents the results of three different QRS detection methods reported to be very reliable. They have been tested using the same ECG databases to make comparison easier. The evaluation complies with the standard ANSI/AAMI EC38/57. Furthermore, the algorithms are compared according to their complexity, their real-time capabilities and their ability to extract other relevant parameters from the ECG signal.

INTRODUCTION

With telemedical applications in constant development, the demand is increasing for the transmission of physiological signals and vital parameters, as well as for the (pre)classification of the signals and automatic initiation of alarms.
The classification methods used in such mobile devices should be very sensitive in order to recognize all relevant events, at the cost of an increased false alarm rate, while classification on stationary systems should filter out virtually all false alarms. As all classification algorithms rely on a very good QRS detection, one has to identify the method best-suited for the use on the mobile system and its stationary counterpart. Most methods found in the literature cannot be directly compared to each other, since they were all tested using different sets of ECG data. A software framework is therefore necessary to test all algorithms under the same conditions in compliance to existing standards, e.g. the ANSI/AAMI standards EC38 and 57 [1], or the corresponding IEC standards.

MATERIALS AND METHODS

Using a software framework implemented under Matlab®/Simulink® [2] for the evaluation of ECG classification algorithms, three different QRS detection algorithms have been implemented and tested. The simulation environment and the data used for testing have been described in an earlier article [3]. Three algorithms have been implemented in the simulation model:

- a non-linear transform called MOBD (Multiplication of Backward Difference), first described by Suppappola and Sun [4], which was expanded upon in [5]
- the well-known Pan/Tompkins algorithm [6], which is a combination of digital filters and non-linear transforms
- a wavelet approach presented by Li et al. [7]

The Multiplication of the Backward Difference (MOBD) can be derived by the formula

$$y(n) = \prod_{k=0}^{4} \left| x(n-k) - x(n-k-1) \right| \qquad (1)$$

QRS detection is performed with a set of adaptive thresholds. Because there is no other signal pre-processing, noise and artifacts have to be additionally detected in the resulting feature signal.
On the contrary, Pan and Tompkins make use of a signal processing stage first using a bandpass filter to eliminate noise from the ECG signal. The filter coefficients are integers for a sampling frequency of 200 Hz. Changing the sample rate would then require the filter coefficients to be re-calculated to maintain filter characteristics. After bandpass filtering, the ECG signal is rectified, squared and integrated using a moving window integrator (MWI). The resulting feature signal is then scanned for peaks and compared against a signal and noise threshold. At each peak, the set of thresholds is re-calculated using the current MWI output signal level. In addition to the original implementation, two changes have also been tested. First, the width of the MWI window was linearly decreased from 35 samples at a heart rate of 100 bpm to eight samples at 200 bpm to enhance QRS detection quality for high beat frequencies. Second, another peak detection algorithm was used, resulting in a less frequent update of threshold sets. This was done to avoid possibly unnecessary threshold updates due to small noise peaks in the MWI signal.
The wavelet approach is based on the detection of singularity points (the R-peaks) with wavelet-equivalent anti-symmetric bandpass FIR filters. The ECG is processed for scales j=1 to 4 and the QRS complex is detected by searching "Modulus Maximum Lines" (MML) in the different scales and comparing their amplitudes and time intervals using a set of detection rules. The implementation of this method inside the simulation framework resembles the one described in the article, except with another frame length (512 instead of 600 ECG points). Also, an overlap of consecutive frames

has been introduced. Because the wavelet-transform is implemented using digital filters, these are constantly applied to the ECG signal and not in a frame-based manner.

RESULTS

Table 1: Test results for all three implemented methods on channel one of the MIT/BIH database. TP indicates the true positive, FP the false positive and FN the false negative detections of the algorithms

Algorithm	TP	FP	FN	Se	+P
MOBD	90236	240	1047	98.85	99.73
Tompkins Original	90432	1331	851	99.07	98.55
Tompkins dynamic MWI	90432	1331	851	99.07	98.55
Tompkins modified peak detection	86687	326	4596	94.97	99.63
Wavelets	89521	5530	1762	98.07	94.18

Table 1 shows the overall results of all implemented methods on channel one of the MIT/BIH database [8]. The MOBD algorithm shows the highest positive predictivity (+P), while the first two implementations of the Tompkins algorithm have a slightly higher sensitivity (Se). The use of less sensitive peak detection in the third Tompkins implementation results in a significant loss of sensitivity (-4.1%) compared to the other two, with only a small increase in positive predictivity.
The performance of the wavelet approach shows the lowest values in both Se and +P of all algorithms, which are also significantly lower than those reported in the literature [7].

DISCUSSION

The MOBD algorithm is the one with the least amount of ECG signal pre-processing. Therefore, the detection delay is very short, but it is also susceptible to signal noise and rapid changes in signal morphology. The detection rules, therefore, have to be chosen very carefully.
The Tompkins algorithm is widely accepted as a standard detection algorithm because of its good detection results and its easy implementation. A drawback is its loss in detection quality when the feature signal has a very low amplitude, like in files 114 and 222 of the MIT/BIH database, where the QRS signal in channel one is very small.
There is no difference in the performance of the original Tompkins algorithm and the MWI dynamic width implementation. This is mostly because of the rather slow heart rates in the MIT/BIH database and will presumably only show an effect if files with long runs of tachycardia are used
The wavelet approach has the most extensive signal preprocessing and may best be implemented on a DSP platform. Due to the small power consumption of modern DSPs, this is not necessarily a criterion for excluding this algorithm in mobile systems. An advantage is the possibility to also use the feature signals for the detection of P- and T-waves, while the other methods require another separate detection method for this task. At the moment, the algorithm shows problems in its sensitivity when paced QRS complexes have to be detected (e.g. files 102 and 104) and low +P values for QRS complexes with QrS or RsR' morphologies (e.g. files 111 and 114).
The detection delay of all three algorithms is suitable for monitoring systems: The MOBD method has the shortest delay (16 ms at 250 Hz sampling rate at best), followed by the wavelet approach (~1.8 seconds at 250 Hz) and the Tompkins algorithm (~2.3 seconds at 200 Hz).

CONCLUSIONS

All three algorithms can be used in mobile systems, but MOBD and Tompkins have fewer hardware requirements. MOBD may be used, if a low detection delay is required, e.g. for cardioversion, and good signal quality can also be assured. Tompkins is well-suited for monitoring, but should be used with at least two-channel recording to avoid decreased sensitivity in low-amplitude ECG. The wavelet approach does not work satisfactorily at the moment. Future enhancements in the current implementation for dealing with the above-mentioned problems are necessary.
Further tests still have to be conducted using other databases [3] and other signal channels to support these conclusions.

REFERENCES

[1] AAMI Standards, EC57: Testing and reporting performance results of cardiac rhythm and ST segment measurement algorithms and EC38: Ambulatory Electrocardiographs, AAMI, Arlington, USA (1998)

[2] The MathWorks, Inc., http://www.mathworks.com

[3] von Wagner G, Kunzmann U, Schöchlin J, Bolz A. Simulation Methods for the Online Extraction of ECG Parameters under Matlab®/Simulink®. Biomedizinische Technik 2002, 47:534-537

[4] Suppappola S, Sun Y. A Comparison of three QRS Detection Algorithms using the AHA ECG Database, IEEE Engineering in Medicine and Biology Society 1991:13, 586-587

[5] Kunzmann U, von Wagner G, Schöchlin J, Bolz A. Parameter extraction of the ECG-signal in real-time. Biomedizinische Technik 2002: 47, 875-878

[6] Pan J, Tompkins, WJ. A Real-Time QRS Detection Algorithm, IEEE Transactions on Biomedical Engineering. 1985:32, 230-236

[7] Li C, Zheng C, Tai C. Detection of ECG Characteristic Points Using Wavelet Transforms, IEEE Transactions on Biomedical Engineering. 1995:42, 21-28

[8] Goldberger AL, Amaral LAN, Glass L, Hausdorff JM, Ivanov PCh, Mark RG, et al. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation 2000:101, 215-220