University of Kuopio Department of Applied Physics Report Series ISSN 0788-4672

High-Resolution QRS Detection Algorithm for Sparsely Sampled ECG Recordings

Timo Bragge, Mika P. Tarvainen, and
Pasi A. Karjalainen

August 31, 2004

Report No. 1/2004

This manuscript has been submitted to *IEEE Trans Biomed Eng*

University of Kuopio • Department of Applied Physics
P.O.Box 1627, FIN-70211 Kuopio, Finland

High-Resolution QRS Detection Algorithm for Sparsely Sampled ECG Recordings

Timo Bragge, Mika P. Tarvainen*, and Pasi A. Karjalainen

August 31, 2004

Abstract A model based high-resolution QRS detection algorithm which is suitable for sparsely sampled ECG recordings is presented. The presented method can be divided into three steps. First, the initial R-wave fiducial points are estimated by using ordinary interpolation methods. Then, the data points of each R-wave are extracted and centered in time and the shape of the R-wave is estimated by nonlinearly fitting a double exponential function to the extracted data points. Finally, the estimated model and its derivative are linearly fitted to the data points of each R-wave separately and new fiducial point estimates are obtained. The proposed method is tested with simulations and real ECG data. As a result, it is observed that the proposed method is suitable also for asymmetric R-waves unlike, e.g., the commonly used cubic spline interpolation method.

Electrocardiogram, heart rate variability, QRS detection, R-wave, sampling rate, modeling, interpolation

1 Introduction

Heart rate variability (HRV) analysis has been widely used for the assessment of the sympathetic and parasympathetic responses of the autonomic nervous system. The HRV time series is generally extracted from the electrocardiogram (ECG) recording by measuring successive RR intervals. The accuracy of the R-wave occurrence time estimates is often required to be about 1 ms and, thus, the sampling frequency of the ECG should be at least 500 Hz [1]. If the sampling frequency of the ECG is less than 500 Hz, the errors in R-wave occurrence times can cause critical distortion to HRV analysis results, especially to spectrum estimates [2, 3]. The distortion of the spectrum is even bigger if the overall variability in heart rate is small [4].

The sampling frequency of the ECG measurement depends on the used instrumentation and data storage. The sampling rate used in some ambulatory ECG recorders can be as low as 100 Hz, whereas high-resolution ECG recorders use sampling rates equal to 1000 Hz or even higher. In the former case, the errors in the R-wave occurrence time estimates can be as large as 5 ms. This is far more than acceptable and, therefore, methods for improving the R-wave detection accuracy are needed.

The most common method for improving the detection accuracy is to use R-wave interpolation. In [5], three different interpolation methods, namely linear, cubic, and spline, were compared. Using the cubic interpolation a resolution of 1 ms and deviation of ± 1 ms in more than 99% of the RR intervals was reported for the sampling rate of 250 Hz. For 100 Hz sampling rate, the same resolution was preserved in 90.5% of the RR intervals.

The interpolation methods are simple to apply and the fiducial point of the R-wave can be estimated with sufficient accuracy from sparsely sampled ECG recordings as far as the shape of the R-wave is close to symmetric. The shape of the R-wave, however, depends, e.g., on the electrode montage used for ECG measurement and also different cardiovascular diseases alter the shape. Thus, the shape of the R-wave may be clearly non-symmetric and the accuracy of interpolation methods is decreased.

*T. Bragge, M.P. Tarvainen, and P.A. Karjalainen are with the Department of Applied Physics, University of Kuopio, Kuopio, Finland.

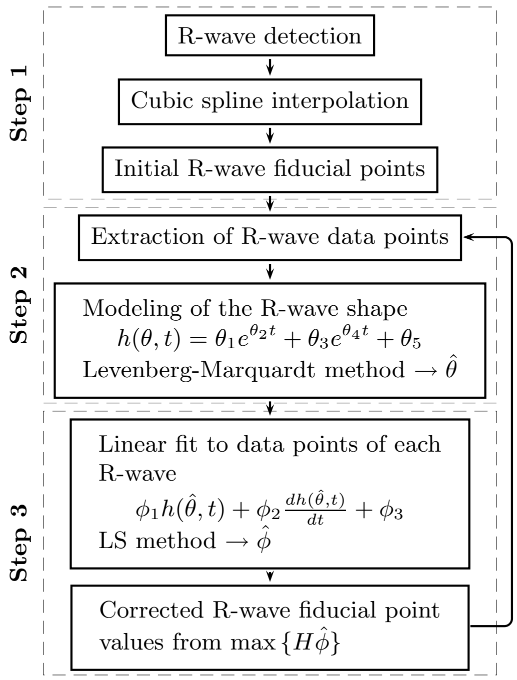


Figure 1: The diagram of the proposed QRS detection algorithm.

In this paper, we propose an advanced QRS detection method which enables accurate estimation of R-wave occurrence times from considerably sparsely sampled ECG recordings. In the proposed method, a model for the R-wave shape is first estimated from the ECG data. The model used for the R-wave is a double exponential model the parameters of which are solved by nonlinear regression methods. The obtained model is then used for estimating the accurate time instant of each R-wave. The accuracy of the proposed method is tested with simulations and real ECG data.

2 Methods

2.1 Description of the method

The proposed method can be divided into three steps: 1) estimation of the initial R-wave fiducial points, 2) extraction of R-wave data points and modeling of the R-wave shape, and 3) correction of the fiducial point values using the estimated model. The second and last steps can be repeated until the fiducial point values converge. An illustrative diagram of the proposed method is presented in Fig. 1 and the three steps are described in details in the following.

2.1.1 Estimation of initial R-wave fiducial points

At first, an adaptive QRS detector algorithm based on the one presented in [6] is applied to detect the R-wave fiducial points from the sparsely sampled ECG recording. The accuracy of the observed time instants is then improved by QRS interpolation (a piecewise cubic spline interpolation with a sampling rate equal to 20 kHz). The observed R-wave maximums after interpolation are taken as initial guesses for R-wave fiducial points.

2.1.2 Modeling the R-wave shape

Once the initial R-wave fiducial points have been estimated the shape of R-wave is modeled. For this, data points from each R-wave are extracted by using a time window centered at the corresponding initial fiducial point values. The data points of each R-wave are then accumulated into analogous temporal frame as presented in Fig. 5 (a). The analogous temporal frame is obtained by subtracting the initial fiducial point instants from the time indices of the corresponding R-wave data points.

After the data points from each R-wave are gathered together, the shape of the individual R-wave can be estimated. We use here a double exponential function

$$h(\theta, t) = \theta_1 e^{\theta_2 t} + \theta_3 e^{\theta_4 t} + \theta_5 \tag{1}$$

as a model for the R-wave shape. The task is then to estimate, in some sense, the optimal values for the model parameters $\theta = (\theta_1, \ldots, \theta_5)$. In the least squares (LS) sense the parameters θ are chosen such that the squared error norm

$$l(\theta) = \|z - h(\theta, t)\|^2 \tag{2}$$

where $z = z(t)$ is a vector containing the R-wave data points, is minimized. This is a nonlinear estimation problem the solution of which can be obtained, e.g., with the Levenberg-Marquardt method

$$\hat{\theta}_{k+1} = \hat{\theta}_k + \lambda \left(J^T J + \alpha I\right)^{-1} J^T \left(z - h(\hat{\theta}_k, t)\right) \tag{3}$$

where J is the Jacobian of $h(\theta, t)$ evaluated at $\hat{\theta}_k$, λ is the step size parameter of the iteration, and $\alpha > 0$ is a scalar parameter the meaning of which is to ensure the stability of the algorithm.

The iteration (3) is repeated until a desired convergence is achieved. The convergence can be evaluated by comparing the norm of the parameter estimates $\hat{\theta}$ with the norm of the increment term. After convergence, an estimate for the shape of the R-wave is obtained as $h(\hat{\theta}, t)$, which is then used for correcting the initial R-wave fiducial point values.

2.1.3 Correction of the R-wave fiducial point values

The final step of the proposed method is to use the estimated R-wave model for correcting the initial fiducial point time instants. This is accomplished through linear LS regression. As regressors we select the estimated model $h(\hat{\theta}, t)$ and its first derivative $dh(\hat{\theta}, t)/dt$. The derivative is included in the regression to enable the shifting of the peak position in time.

In order to find to corrected fiducial point values, the estimated model and its derivative are fitted into the data points of each R-wave separately. That is, the data points z^j of j'th R-wave are presented as a linear combination

$$z^j = H^j \phi^j = \phi_1^j h(\hat{\theta}, t^j) + \phi_2^j \frac{dh(\hat{\theta}, t^j)}{dt} + \phi_3^j \tag{4}$$

where t^j are the time indices related to the j'th R-wave. The parameters ϕ^j can be solved in LS sense as

$$\hat{\phi}^j = ({H^j}^T H^j)^{-1} {H^j}^T z^j \tag{5}$$

and the R-wave estimate as

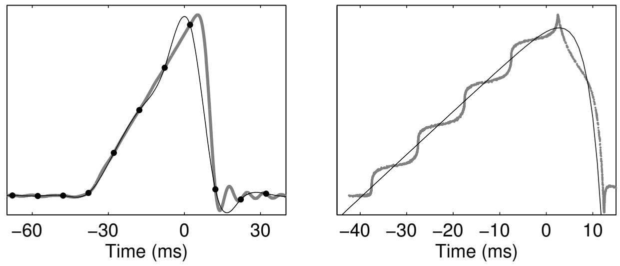
$$\hat{z}^j = H^j \hat{\phi}^j. \tag{6}$$

By evaluating H^j in a dense time grid the maximum of $\hat{z}^j$ can be used as the corrected time instant for the R-wave fiducial point.

The fitting procedure, i.e. equations (4)-(6), are repeated for every R-wave. The accuracy of the obtained fiducial point estimates can be improved by iterating steps 2 and 3 for few times. That is, consider the corrected time instants as initial values in step 2 and re-evaluate the model $h(\theta, t)$ and then use this adjusted model in the fitting procedure of step 3 for obtaining new fiducial point estimates. The iteration is expected to converge quickly in few iterations.

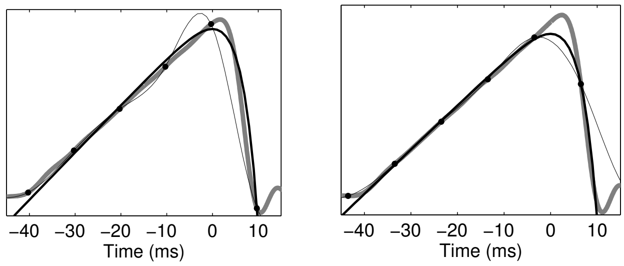
2.2 Data acquisition

The simulated data was constructed using the Matlab® `pulstran` function. This function generates pulse trains from prototype functions. For a prototype function, a nonsymmetric triangle was generated using the `tripuls` function. The interval between consecutive pulses was taken randomly from a uniform distribution on the interval [0.8,1.2] seconds. The simulated pulse train was sampled at 20 kHz. The obtained signal was then filtered with a 150 Hz low-pass filter in order to smooth



(a) (b)

Figure 2: Modeling of the simulated waveform. (a) Initial peak instant estimate: the true waveform (▬), its 100 Hz sampled data points (•), and cubic spline interpolation (—). (b) Data points of each waveform centered according to the spline interpolation maximums (·) and the fitted double exponential function (—).



(a) (b)

Figure 3: Two sample cases (a) and (b) of peak estimation for simulated data. The true waveform (▬), its 100 Hz sampled data points (•), cubic spline interpolation (—), and the fitted double exponential function according to the proposed method (**—**).

the peaks of the triangle pulses. The simulated data sequence was then resampled at 100 Hz. The length of the generated data sequence was equal to 500 seconds and it contained 500 peaks.

The ECG was recorded using a NeuroScan system (Compumedics Limited) with the new SynAmps^2 amplifier. The sampling rate of the system was set to 20 kHz. The baseline of the ECG signal was removed by fitting a third order curve to the data. The measured ECG was then low-pass filtered using a 7th order elliptic filter with a cut-off frequency equal to 300 Hz. The aim of low-pass filtering was to smooth the R-wave peaks to enable an unambiguous fiducial point estimates. Finally, a sparsely sampled ECG signal was obtained from the 20 kHz recording by resampling it at 100 Hz. The length of the ECG recording was approximately 10 minutes and it contained a little bit over 700 beats.

3 Results

3.1 Simulation results

The proposed method was first tested with the simulated data sequence described above. The waveform of the simulated data is presented in Fig. 2 (a), which describes the first step of the proposed method. That is, the initial guess for the peak instant is obtained from the maximum of a cubic spline interpolation. For a highly asymmetric waveform the spline interpolation tends to make the peak more symmetric and thus the observed peak instant is clearly biased as can be seen from Fig. 2 (a).

In the next step, the data points of each peak were extracted and centered according to the initial peak instant estimates. A time window equal to [-40,10] ms was applied. The double

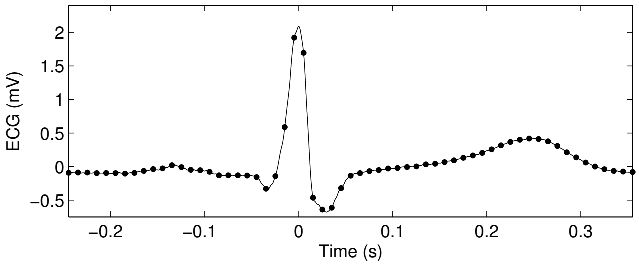


Figure 4: A sample of the 20 kHz sampled ECG (—) and its 100 Hz sampled data points (●).

TABLE I: Statistics of absolute peak instant estimation errors for the peak picking, cubic spline interpolation, and proposed method

Estimation errors (ms)	Peak picking	Cubic spline	Proposed method
Simulated data sequence			
Mean	3.04	3.71	1.81
SD	2.13	1.69	0.84
Real ECG data sequence			
Mean	2.62	0.79	0.49
SD	1.58	0.38	0.56

exponential function (1) was then fitted to the data points using the Levenberg-Marquardt method given in (3). This step is presented in Fig. 2 (b).

In the final step, the estimated double exponential function is used for correcting the initial peak instants according to equations (4)-(6). Two sample cases of this step are presented in Fig. 3, where the fit to data points of single peaks is shown along with the true peak waveform. For comparison, the cubic spline interpolations are also shown for the two peaks. The presented fits are obtained after few iterations of steps 2 and 3 when the parameters of the double exponential function have converged.

The statistics of the peak instant estimation errors were then calculated. The estimation errors were obtained by subtracting the estimated peak instants from the true ones (instants obtained from the 20 kHz sampled data). The mean and standard deviation (SD) of the absolute values of the errors are presented in Table I. For comparison, the same statistics were also calculated for the cubic spline interpolation and peak picking (peak instants straight from 100 Hz data) methods. It is observed that the errors for the proposed method are clearly smaller that those for the spline interpolation. Especially, the bias of the proposed method is much smaller than that of the spline interpolation.

3.2 Real ECG data experiments

After simulations, the proposed method was tested with real ECG data. The sampling rate of the ECG signal was originally 20 kHz, but it was resampled at 100 Hz for the analysis. A sample waveform of the measured ECG is presented in Fig. 4. It is observed that the waveform is slightly asymmetric. The time window used for R-wave data point extraction was now set to [-20,10] ms. The nonlinear fit to the extracted R-wave data points is presented in Fig. 5 (a) and an example of the fiducial point estimation using the estimated model is presented in Fig. 5 (b).

The same statistics as for the simulated data were then calculated for the obtained R-wave fiducial point estimates. Obtained statistics for the proposed method, spline interpolation, and peak picking are presented in Table I. It is again observed that the proposed method has smaller

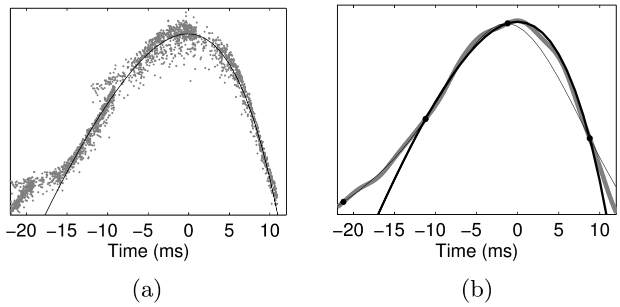


Figure 5: Real ECG data experiment. (a) The fit of the double exponential function to the R-wave data points (·). (b) Estimates of R-wave fiducial point: true R-wave shape (▬), its 100 Hz sampled data points (•), cubic spline interpolation (—), and the fitted double exponential function according to the proposed method (**—**).

bias than the spline interpolation, even though the SD is now bigger for the proposed method.

4 Discussion

We have proposed an advanced QRS detection algorithm to be used for relatively sparsely sampled ECG recordings. Using the proposed method accurate R-wave fiducial point estimates can be obtained even from extremely low sampled ECG recordings. The proposed method is computationally much more complex than the typically used methods such as the cubic spline interpolation. The main benefit of the method is, however, that it works also for nonsymmetric R-waves. This is not the case for spline interpolation, since it tends to symmetry causing a clear bias in peak estimates in nonsymmetric case [see Fig. 2 (a) and Table I]. On the other hand, if the R-wave is symmetric enough the proposed method results in approximately the same accuracy as the spline interpolation and, therefore, its use may be more or less pointless due to its complexity.

The most sensitive part in the proposed method is the selection of the R-wave data points which are to be used in model estimation. That is, the selection of the points presented in Fig. 5 (a). If too many data points are included the double exponential function can not anymore model the R-wave shape in adequate accuracy. However, data points from both sides of the R-wave peak need to be included. In this paper we used a time window equal to [-20,10] ms, which gives three to four data points from each R-wave for the 100 Hz sampling rate.

In the future, the most interesting task would be to construct a more complex model for the R-wave shape that would enable a more accurate estimation of diverse waveshapes. Then also more data points could probably be included in the estimation and the accuracy of the method could be improved thereby. Our intension is also to apply the method to noninvasive continuous blood pressure recordings (measured using the Portapres device), since the blood pressure waveform is typically clearly asymmetric in shape and, thus, the proposed method would enable accurate estimates of systolic time instants even from rather sparsely sampled recordings.

References

[1] Task force of the European society of cardiology and the North American society of pacing and electrophysiology, "Heart rate variability – standards of measurement, physiological interpretation, and clinical use," *Circulation*, vol. 93, no. 5, pp. 1043–1065, March 1996.

[2] M. Merri, D. Farden, J. Mottley, and E. Titlebaum, "Sampling frequency of the electrocardiogram for spectral analysis of the heart rate variability," *IEEE Trans Biomed Eng*, vol. 37, no. 1, pp. 99–106, January 1990.

[3] M. García-González, M. Fernández-Chimeno, and J. Ramos-Castro, "Bias and uncertainty in heart rate variability spectral indeces due to the finite ECG sampling frequency," *pm*, vol. 25, no. 2, pp. 489–504, April 2004.

[4] G. Pinna, R. Maestri, A. D. Cesare, R. Colombo, and G. Minuco, "The accuracy of power-spectrum analysis of heart-rate variability from annotated RR lists generated by Holter systems," *Physiol Meas*, vol. 15, pp. 163–179, 1994.

[5] I. Daskalov and I. Christov, "Improvement of resolution in measurement of electrocardiogram RR intervals by interpolation," *Med Eng Phys*, vol. 19, no. 4, pp. 375–379, June 1997.

[6] J. Pan and W. Tompkins, "A real-time QRS detection algorithm," *IEEE Trans Biomed Eng*, vol. 32, no. 3, pp. 230–236, March 1985.