A SIMPLIFIED QRS DECISION STAGE BASED ON THE DFT COEFFICIENTS

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ABSTRACT

This paper shows an adaptive statistical test for QRS detection of ECG signals. The method is based on a M-ary generalized likelihood ratio test (LRT) defined over a multiple observation window in the *Fourier domain*. The previous algorithms based on maximum *a posteriori* (MAP) estimation result in high signal model complexity which i) makes them computationally unfeasible or not intended for real time applications such as intensive care monitoring and (ii) in which the parameter selection conditions the overall performance. A simplified model based on the independent Gaussian properties of the DFT coefficients is proposed. This model allows to define a simplified MAP probability function and to define an adaptive MAP statistical test in which a global hypothesis is defined on particular hypotheses of the multiple observation window. Moreover, the observation interval is modeled as a discontinuous transmission discrete-time stochastic process avoiding the inclusion of parameters that constraint the morphology of the QRS complexes.

Index Terms— Electrocardiogram (ECG), QRS detection, M-ary Likelihood Ratio Test.

1. INTRODUCTION

One of the most relevant waveforms in the electrocardiogram (ECG) is the QRS complex since it has been used in several medical applications such as noise cancelation, automated determination of heart rate or computer-based arrhythmia monitoring [1, 2]. The QRS complex reflects the electrical activity during ventricular contraction, thus the time of its occurrence as well as its shape provide relevant diagnostic and prognostic information in clinical practice [3]. In the past decades several approaches to QRS detection based on different paradigms have been successfully proposed. Examples of such approaches are based on the field of artificial neural networks, genetic algorithms, wavelet transform or filter banks, as well as other heuristic non linear transforms [2]. Most QRS detectors have been developed following a three-step structure [2], that is, a linear filter suppressing noise and artifacts followed by a nonlinear transformation for signal enhancement. The output of these two stages is then fed to the third decision rule stage for detection. The main target of this paper is focused on the third stage, therefore the proposed method could be used in combination with detectors described in the literature which have been developed from *ad hoc* reasoning and experimental insight.

Up to our knowledge the first approach based on maximum *a posteriori* (MAP) estimation for QRS detection was proposed in [4]. This method was computationally unfeasible, thus additional simplifications and approximations on the MAP estimation were needed to be introduced to reduce the computation time [5], but still the method could not be considered as a real time approach, i.e. the estimation of arrival times are not necessary found in temporal order [5]. On the other hand, the asymptotic properties of the Discrete Fourier Transform (DFT) coefficients [6] could be analyzed as well in the definition of the signal model, i.e. they are defined as independent Gaussian variables. If these assumptions are considered in context,f an effective and *real-time* M-ary LRT detector could be derived with a less number of parameters to be estimated, i.e. only the variances of the noise and desired signal [7].

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2. MAP LRT ADAPTIVE QRS DETECTION

2.1. Signal Model

The ECG signal is modeled as a discrete-time stochastic process [5]; typically, the observation signal for a real time QRS detector is given by:

$$x(n) = \begin{cases} B \cdot s(n-\theta) + v(n), & q = 1 \\ v(n), & q = 0 \end{cases} \quad \text{for} \quad n = 0, \dots, N-1 \tag{1}$$

where $s(n)$ is the QRS complex with known morphology (pulse-shaped waveform), arrival time θ, amplitude B and width D which is corrupted by a stationary, white, Gaussian process $v(n)$ with variance σ_v^2. The Fourier expansion coefficients of the observed signal are assumed to be statistically independent Gaussian random variables. These coefficients are obtained by decomposing the signal into overlapped frames each of size $N_w < N$ with a S_w-sample window shift and by computing the J-point windowed DFT spectral representation on a frame by frame basis:

$$X_j(k) = \frac{1}{\|w\|}\sum_{m=0}^{N_W-1} x(jS_w{+}m)w(m)e^{\frac{-j2\pi mk}{J}}; \forall k = 0, ..., J{-}1 \quad (2)$$

where j denotes the frame index, w represents the window (typically, a Hamming window to reduce the correlation between widely separated spectral components) and $\|w\|$ is its norm. Thus, $|X_j(k)|^2$ is a consistent estimation of the power spectral density (PSD) of the signal. In the Fourier domain the observation window can be rewritten as:

$$\mathbf{X}_j = \begin{cases} \mathbf{S}_j + \mathbf{V}_j, & q = 1 \\ \mathbf{V}_j, & q = 0 \end{cases} \quad (3)$$

Thus, once the window size N_w is selected, the channel can be described as a vector sequence $\mathbf{X}_j$ that alternates between two possible states, i.e. presence or absence of pulse-shaped waveforms. Assuming that the total number of observations is $\lfloor \frac{N-N_w}{S_w} \rfloor + 1 = 2L + 1$ and the number of signal observations is $\lfloor \frac{N_w+D}{S_w} \rfloor = 2Q + 1$, the partial observation vectors can be re-indexed and grouped into a global observation matrix (from now on *buffer*): $\widehat{\mathbf{X}} = \{\mathbf{X}_{l-L}, \ldots, \mathbf{X}_{l-Q}, \ldots, \mathbf{X}_l, \ldots \mathbf{X}_{l+Q}, \ldots, \mathbf{X}_{l+L}\}$.

2.2. Detector Structure based on MAP M-ary LRT

Given the signal model, the probability for each observation vector can be evaluated under binary hypothesis testing as:

$$p(\mathbf{X}_j|h_j) = \begin{cases} \prod_{k=0}^{J-1} \frac{1}{\pi(\lambda_V(k) + \lambda_S(k))} \\ \cdot \exp\left\{-\frac{|X_j(k)|^2}{(\lambda_S(k) + \lambda_V(k))}\right\} & ; h_j = 1 \\ \prod_{k=0}^{J-1} \frac{1}{\pi\lambda_V(k)} \exp\left\{-\frac{|X_j(k)|^2}{\lambda_V(k)}\right\} & ; h_j = 0 \end{cases} \quad (4)$$

where $h_j = \{0, 1\}$ is the partial hypothesis, that is, the presence or absence of the QRS complex in the observation vector $\mathbf{X}_j$ and $\lambda_S(k)$ and $\lambda_V(k)$ are the PSDs of the QRS and noise processes, respectively. Given that the observation vectors $\mathbf{X}_j$ in the $\widehat{\mathbf{X}}$ buffer are statistically independent, $\mathbf{H}_0$ and $\mathbf{H}_1$ denote the set of hypotheses (or *states*) $\mathbf{h}$ that depends on the $2r + 1$ partial hypotheses formulated on the central frames of the buffer and $p(\widehat{\mathbf{X}}, \mathbf{H_1})$ and $p(\widehat{\mathbf{X}}, \mathbf{H_0})$ the joint probabilities, a MAP optimum criterion is defined to be an M-ary LRT (with $M = 2L + 1$) as follows:

$$\Gamma \equiv \frac{p(\widehat{\mathbf{X}}|\mathbf{H}_1)}{p(\widehat{\mathbf{X}}|\mathbf{H}_0)} = \frac{p(\widehat{\mathbf{X}}, \mathbf{H}_1)}{p(\widehat{\mathbf{X}}, \mathbf{H}_0)} = \frac{\sum_{\mathbf{h}\in\mathbf{H}_1} p(\mathbf{h}) \prod_{j=1}^{M} p(\mathbf{X}_j|h_j)}{\sum_{\mathbf{h}\in\mathbf{H}_0} p(\mathbf{h}) \prod_{j=1}^{M} p(\mathbf{X}_j|h_j)} \underset{H_0}{\overset{H_1}{\gtrless}} \eta \quad (5)$$

where the decision threshold η is used to tune the operating point of the detector and $p(\mathbf{h})$ is the *a-priori* probability of hypothesis $\mathbf{h}$. Thus, it is required to estimate the *a priori* probability of the states, that can be easily measured analyzing the proportions of QRS segments on an ECG template. If (5) is approximated by taking the maximum log value of the hypotheses, a revised statistical test can be defined in matrix form removing the summation symbols as:

$$\log\Gamma^* = \max(\mathbf{H}_1\mathbf{B}_1 + (\mathbf{J_1} - \mathbf{H_1})\mathbf{B_0} + \mathbf{P_1}) \\ - \max(\mathbf{H}_0\mathbf{B}_1 + (\mathbf{J_0} - \mathbf{H_0})\mathbf{B_0} + \mathbf{P_0}) \underset{H_0}{\overset{H_1}{\gtrless}} \eta \quad (6)$$

where $\mathbf{H}_k$ is the $K \times M$ row-wise matrix of states $\mathbf{h}$, $\mathbf{B}_k \equiv [\log p(\mathbf{X}_1|h_1), \log p(\mathbf{X}_2|h_2), ..., \log p(\mathbf{X}_M|h_M)]^{\mathrm{T}}$, $\mathbf{P}_k \equiv [\log(p(\mathbf{h}_1)), \ldots, \log(p(\mathbf{h}_K))]^T$, $\mathbf{h_j} \in \mathbf{H_k}$ is the column vector of the logarithmic *a priori* probabilities of the hypotheses in $\mathbf{H}_k$ and $\mathbf{J_k}$ is the $K \times M$ matrix of ones. The value $K = 2(L - r) + 1$ depends on how the sets $\mathbf{H_0}$ and $\mathbf{H_1}$ are defined.

2.3. Estimation of Statistical Parameters

In a real time QRS detector the processing to be performed on the incoming signal $x(n)$ is divided into two phases: i) delimitation of the observation window that should *not exceed the size of the ECG signal period*, i.e. it should not include two QRS complexes; ii) estimation of the model parameters in (4), i.e. $\lambda_S(k) \equiv E\{|S(k)|^2\}$ and $\lambda_V(k) \equiv E\{|V(k)|^2\}$.

2.3.1. Noise Spectrum Estimation

An initial model for the noise spectrum should be determined from the incoming signal. To this purpose, fiducial points are computed for a few initial periods of the ECG signal following the procedure described in [8]. Once the isoelectric line is determined, the noise spectrum $V_j(k)$ is backward computed from these knots and smoothed by averaging [6]. Moreover the noise spectrum is then updated, in a similar fashion of the recursive averaging method proposed in [6], during the *non-QRS* periods (determined by the detector) by means of a 1st order IIR filter on the smoothed spectrum:

$$V_j(k) = \lambda_v V_{j-1}(k) + (1 - \lambda_v)X_j(k) \quad (7)$$

where $\lambda_v = 0.98$.

2.3.2. QRS Spectrum Estimation

The clean QRS spectrum is estimated by combining smoothing, spectral subtraction and conventional two-stage mel-warped Wiener filter design [9]. The latter attempts to remove additive noise throughout two filtering stages: the first stage coarsely reduces noise and whitens residual noise; the second stage removes any residual noise.

$$S_j(k) = \lambda_s S'_{j-1}(k) + (1 - \lambda_s) \cdot \max(X_j(k) - V_j(k), 0) \quad (8)$$

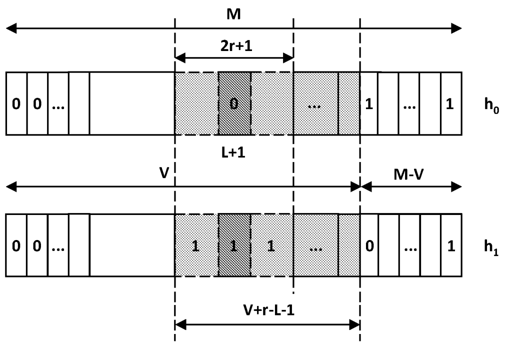

Fig. 1. Hypothesis considered for the derivation of the approximate M-ary LRT and its expected value. The most probable hypotheses in $\mathbf{H_0}$ and $\mathbf{H_1}$ for a non-QRS to QRS transition.

where $\lambda_s = 0.99$. Then the Wiener filter $H_j(k)$ is designed as:

$$H_j(k) = \frac{\eta_j(k)}{1+\eta_j(k)}; \text{ where } \eta_j(k) = \max\left(\frac{S_j(k)}{V_j(k)}, \eta_{min}\right). \quad (9)$$

where η_{min} is selected so that the filter yields a 20 dB minimum attenuation. Finally the clean QRS spectrum is computed as $S'_j(k) = H_j(k)X_j(k)$. The latter filter design process is repeated twice [9]. With these operations we derive the ML estimators of the k-th signal spectral component variance $(\lambda_S(k), \lambda_V(k))$ in the j-th analysis frame which have been successfully used in other fields such as speech enhancement [6].

3. APPROXIMATE LOG M-ARY LRT ESTIMATION

For a simplification of (6) a particular transition is analyzed (see figure 1). This corresponds to a situation where $M-V$ observations in the buffer of size $M = 2L+1$ are QRS frames from a total of $2Q+1$ QRS frames. The most probable hypotheses in $\mathbf{H_0}$ and $\mathbf{H_1}$, denoted by $\mathbf{h_0} = \{h_{1,0}, \ldots, h_{M,0}\}$ and $\mathbf{h_1} = \{h_{1,1}, \ldots, h_{M,1}\}$ respectively, are evaluated by taking the max logarithms in (5):

$$\log\Gamma^* = \log p(\mathbf{h}_1) + \textstyle\sum_{j=1}^{M} \log p(\mathbf{X}_j|h_{j,1}) - \log p(\mathbf{h}_0) \\ - \textstyle\sum_{j=1}^{M} \log p(\mathbf{X}_j|h_{j,0}) \underset{H_0}{\overset{H_1}{\gtrless}} \log\eta$$

or equivalently for $\eta = 1$:

$$\log\Gamma^* = \sum_{j=1}^{M} \log p(\mathbf{X}_j|h_{j,1}) - \log p(\mathbf{X}_j|h_{j,0}) \underset{H_0}{\overset{H_1}{\gtrless}} \log\frac{p(\mathbf{h}_0)}{p(\mathbf{h}_1)} \quad (10)$$

Deleting the partial states of $\mathbf{h_1}$ and $\mathbf{h_0}$ in common that is $h_{j,1} = h_{j,0}$ it leads to:

$$\log\Gamma^* = \log\prod_{j=L+1-r}^{V} \frac{p(\mathbf{X}_j|1)}{p(\mathbf{X}_j|0)} \underset{H_0}{\overset{H_1}{\gtrless}} \log\frac{p(\mathbf{h}_0)}{p(\mathbf{h}_1)} \quad (11)$$

By defining the subset Ω of indexes where j is evaluated (shaded in light gray in figure 1) and substituting equation (4) in the previous equation, the decision rule is finally defined as

$$\log\Gamma^* = \sum_{j\in\Omega}\sum_{k=0}^{J-1}\left(\frac{\gamma_{k,j}\xi_{k,j}}{1+\xi_{k,j}} - \log(1+\xi_{k,j})\right) \underset{H_0}{\overset{H_1}{\gtrless}} \log\frac{p(\mathbf{h}_0)}{p(\mathbf{h}_1)} \quad (12)$$

where $\xi_{k,j} \equiv \frac{\lambda_S(k)}{\lambda_V(k)}$ is the *a-priori* SNR for the k-th band and $\gamma_{k,j} \equiv \frac{|\mathbf{X}_j(k)|^2}{\lambda_V(k)}$ denotes the *a-posteriori* SNR for the k-th band at the j-th frame of the buffer. In addition, a scaled decision rule independent of Ω and J:

$$\log\Gamma^* = \frac{1}{JK}\sum_{j\in\Omega}\sum_{k=0}^{J-1}\left(\frac{\gamma_{k,j}\xi_{k,j}}{1+\xi_{k,j}} - \log(1+\xi_{k,j})\right) \quad (13)$$

is preferred, where $K = V - L + r - 1$ is the cardinality of Ω. This statistical test can be understood as an average of the decision criterion over the selected frames present in the buffer. Finally, from (13) the expected value can be computed:

$$E\{\log\Gamma^*\} = \frac{1}{JK}\sum_{j\in\Omega}\sum_{k=0}^{J-1}\left(\frac{E\{\gamma_{k,j}\}\xi_{k,j}}{1+\xi_{k,j}} - \log(1+\xi_{k,j})\right) \quad (14)$$

By using $E\{\gamma_{k,j}\} = \begin{cases}(1+\xi_{k,j}) & ; M-V > V \\ 1 & ; M-V < V\end{cases}$ and assuming stationary white noise and signal models (the SNRs are constant for all the frequency bands k) it yields:

$$E\{\log\Gamma^*\} = \begin{cases}\xi - \log(1+\xi) & ; M-V > V \\ \frac{\xi}{1+\xi} - \log(1+\xi) & ; M-V < V\end{cases} \quad (15)$$

Under this naive approximation based on Gaussian processes the proposed M-LRT may effectively discriminate between QRS and noise frames for a wide range of SNRs during step transitions in the observation window. Figure 2 shows an example of the database [10] and the result of the proposed QRS detector an overlap of 25% between consecutive windows. The selection of the size of the window influences the performance of any detector since it controls the amount of information processed in the test. Typically the QRS complex lasts for about $t_{QRS} = 70 - 110$ ms thus a suitable selection for the observation window is $N = t_{QRS} \cdot F_s \sim 40$ samples.

4. EXPERIMENTS AND DISCUSSION

The proposed detector was mainly evaluated in terms of the ability to discriminate between QRS and non-QRS periods at different noise scenarios and SNR levels. Several standard ECG databases are available for the evaluation of software QRS detection algorithms [2]. One of these databases is the MIT-BIH database [10], provided by MIT and Boston's Beth Israel Hospital which consists of ten databases for various test

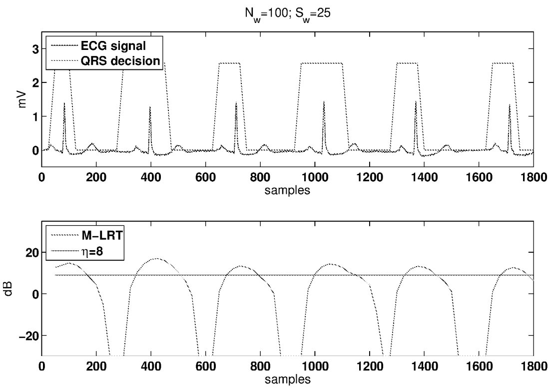

Fig. 2. Patient 101 of the database [10] sampled with $F_s = 360Hz$. A 25% overlap between observation windows is selected. The M-ary LRT test is performed with M=3.

purposes. The experiments in this paper focus on the Arrhythmia Database which contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied between 1975 and 1979. The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range where several cardiologists independently annotated each record [10], altogether there are about 116137 QRS complexes. While some records contain clear R-peaks and few artifacts (e.g. records 100-107), for some records the detection of QRS complexes is very difficult due to abnormal shapes, noise and artifacts (e.g., records 108 and 207).

4.1. Performance Measures

The usage of software QRS detection algorithms in medical devices requires the evaluation of the detection performance on standard databases. According to [11], essentially two parameters should be used to evaluate the algorithms; that is, $S = \frac{T_P}{T_P+F_N}$; $P_L = \frac{T_P}{T_P+F_P}$ where S denotes the sensitivity, P_L the positive likelihood, T_P the number of true positive detections, F_N the number of false negatives, and F_P the number of false positives.

Two MAP decision methods are evaluated on the standard MIT-BIH database in order to get comparable and reproducible results. The former is based on a real time implementation of the matched-filter proposed in [4]. This approach is applied to an observation window comparable with the one used by the other QRS M-ary detector (delimitation of the observation interval), thus the method is converted into a real time detector provided that the application of the original approach to the MIT-BIH records is computationally unfeasible. Furthermore, we are focussing our attention in the decision rule stage, that is, the methods based on MAP decision, since they form a general framework and could be used in conjunction with other approaches such as linear filtering, non-linear

Table 1. Operation points for the MAP based QRS detectors. Average and deviation of S and P_L ($N_w = 40$, $S_w = 10$)

	$\hat{S}$	σ_S	$\hat{P_L}$	σ_{P_L}
1-ary LRT	**0.9386**	**0.0852**	**0.9105**	**0.1201**
3-ary LRT	**0.9418**	**0.0769**	**0.9458**	**0.0816**
5-ary LRT	**0.9700**	**0.0432**	**0.9141**	**0.1035**
7-ary LRT	**0.9761**	**0.0625**	**0.8936**	**0.1075**
matched filter	0.9567	0.0596	0.8915	0.1458

transformations or heuristics based procedures for the same detection problem. The model parameters are selected with values $N_w = \{40, 100\}$ and $S_w = \{10, 25\}$ samples, respectively. The order of the model is selected to be $L = \{1, 2, 3\}$, therefore the size of the observation interval is $\{70, 175\}$ up to $\{110, 275\}$ samples. Note that the typical P-QRS-T interval duration is about 530 ms ($\sim$ 190 samples at 360 Hz) thus the last value is clearly out of this bound. The matched filter used as the baseline method is defined in the time domain as a *perfect replica* of a QRS template using a synthesized ECG signal. Thus, the classical method has been designed under the more favorable conditions by using a time-reversed template of the waveform. The maximization of the log function is carried out on the arrival time θ among all possible values in the observation window.

The results of this comparison are shown in table 1, where the S and the P_L of the proposed and the baseline methods at the operation point are shown. It is clearly shown that, while the revised method yields similar QRS detection accuracy when compared to the matched filter based detector [4] at low model order, it exhibits an improved accuracy in detecting QRS periods when the order is increased, i.e $M = 7$. The improvements are especially important for poor SNRs and the presence of artifacts or abnormal QRS shapes. Using the other combination in the delimitation of the observation interval, i.e. $N_w = \{100\}$ and $S_w = \{25\}$ yields similar results to those explained before, that is increasing the model order provides an increase in the detection performance except when $M = 9$ since the observation interval does not fulfill the assumptions held in section 2.3, i.e. it contains 325 samples ($\sim$ 900 ms) thus two QRS complexes may be included in it. As a conclusion it is shown that the M-ary LRT method yields a significant improvement in S, and in P_L when the model order is greater than three $M > 3$ and provides similar results as a trade-off between those measures when compared to the baseline. Moreover, from this analysis the proposed detector scheme for $M = 5$ achieves the best compromise among the different detectors tested. It yields good results in detecting QRS and non-QRS periods and exhibits a very slow performance degradation at unfavorable noise conditions in QRS detection.

4.2. Receiver Operating Characteristics Curves

The ROC (receiving operating characteristic) curves have shown to be very effective for the evaluation of QRS detectors [2, 4, 5]. These plots, which show the trade-off between the error probabilities of QRS and non-QRS detection as the threshold η varies, completely describe the detector error rate. However, the evaluation using the ROC curves requires a subset of cases or measures under the same acquisition conditions, i.e. SNR. Thus, averaging the statistical measures over the records of the database could be also slightly biased as an assessment procedure. Figure 3 shows the P_l versus the false alarm rate ($FAR_0 = 1 - S$) for all the records of the MIT-BIH database under several noise conditions. The proposed method yields better results than the previous MAP method for $M = 7$ and similar results for other detector configurations.

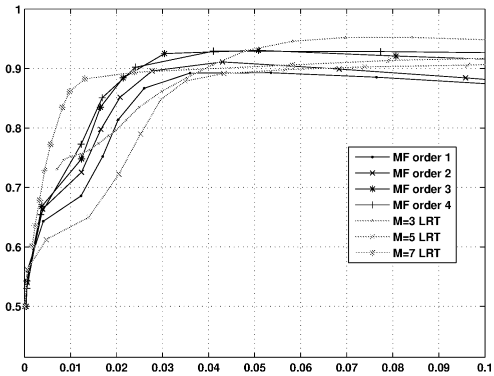

Fig. 3. Zoom on the ROC curves by averaging all the tapes in the database

5. CONCLUSIONS

The use of a M-ary statistical LRT based approach to QRS detection is analyzed in this paper. The performance of the proposed approach is fairly compared to a real time implementation of the classical matched filter method by means of the MIT-BIH database consisting of an heterogenous database in QRS morphologies, type of noise, etc. Defining a suitable observation interval, both detectors provide similar detection rates but under different parameter tuning conditions. The classical method requires the selection of a perfect time-reversed desired waveform to effectively perform in QRS detection, among a large number of parameters [4], while the parameter tuning of the proposed method is much simpler.

6. ACKNOWLEDGEMENTS

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REFERENCES

[1] N.V. Thakor and Yi-Sheng Zhu, "Applications of adaptive filtering to ecg analysis: noise cancellation and arrhythmia detection," *Biomedical Engineering, IEEE Transactions on*, vol. 38, no. 8, pp. 785–794, 1991.

[2] B.-U. Kohler, C. Hennig, and R. Orglmeister, "The principles of software qrs detection," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 21, no. 1, pp. 42–57, 2002.

[3] Romeo Vecht, Nicholas Peters, and Micheal A. Gatzoulis, "Pericarditis, myocarditis, and metabolic disorders," in *ECG Diagnosis in Clinical Practice*, pp. 187–194. Springer London, Jan. 2009.

[4] P.O. Borjesson, O. Pahlm, L. Sornmo, and Mats-erik Nygards, "Adaptive QRS detection based on maximum a posteriori estimation," *IEEE Transactions on Biomedical Engineering*, vol. BME-29, no. 5, pp. 341–351, 1982.

[5] L. Sornmo, Olle Paklm, and Mats-erik Nygards, "Adaptive qrs detection: A study of performance," *Biomedical Engineering, IEEE Transactions on*, vol. BME-32, no. 6, pp. 392–401, 1985.

[6] Y. Ephraim and D. Malah, "Speech enhancement using a minimum mean-square error short-time spectral amplitude estimator," *IEEE Trans. on Acoustics, Speech and Signal Processing*, vol. ASSP-32, pp. 1109–1121, 1984.

[7] J. Ramirez, J. C. Segura, J. M. Gorriz, and L. Garcia, "Improved voice activity detection using contextual multiple hypothesis testing for robust speech recognition," *Audio, Speech, and Language Processing, IEEE Transactions on*, vol. 15, no. 8, pp. 2177–2189, 2007.

[8] C.R. Meyer and H.N. Keiser, "Electrocardiogram baseline noise estimation and removal using cubic splines and state-space computation techniques," *Comput Biomed Res.*, vol. 10, no. 5, pp. 459–470, 1977.

[9] Anshu Agarwal and Yan Ming Cheng, "Two-stage mel-warped wiener filter for robust speech recognition," in *in Proc. ASRU*, 1999, pp. 12–15.

[10] Goldberger A.L. et al., "Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals," *Circulation*, vol. 23, no. 101, pp. 215–220, 1984.

[11] AAMI, "Ansi/aami ec57: Testing and reporting performance results of cardiac rhythm and st segment measurement algorithms," Tech. Rep. EC57-293, American National Standard Inst., 1998.