A NONLINEAR DYNAMICAL MODEL FOR COMPRESSION AND DETECTION OF ECG DATA

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ABSTRACT

We propose a low-dimensional nonlinear model explaining the ECG dynamics, suitable for data compression and possibly feature detection. Tests on real clinically measured ECG signals confirmed very good performance of the model in terms of modeling errors and compression ratio.

1 INTRODUCTION

The Electrocardiogram (ECG) is a recording (measurement) of the electrical activity generated by the heart carried out using sensors positioned on the body surface. Analysis of this signal provides the most common non-invasive method to diagnose cardiac disfunctions. With the development of computerized electrocardiography a wide range of applications have been already implemented, e.g. ambulatory ECG for the detection of heart block transients, real time patient monitoring in coronary care units and intensive care units, etc...

The recent advances in the development of mobile communications is now making feasible and affordable the concept of long distance real time patient monitoring. However, due to the large amount of data collected at an ECG recording, compression is essential for increasing the storage and transmission efficiency.

The analysis and the compression aspect can be connected by using a well adapted signal model, that ideally describes the signal by a small number of meaningful parameters, thus both achieving compression and feature analysis. In the past, a number of parametric and non-parametric methods to analyze and compress ECG signals have been proposed [3-11,13].

In this paper, we propose a nonlinear model, and we show that

- a simple time domain model can accurately describe the dynamics of the ECG
- from a modeling perspective, the ECG cycle is composed of a P, QRS and a T-wave
- a relatively small number of parameters is sufficient to encode one ECG beat

In the following we will present the proposed ECG time domain model, discuss the identification of it's parameters and assess the compression ratio performance of the model.

2 ECG TIME DOMAIN MODEL

Starting from the interpretation of the ECG waves as the solution of a wave equation, we propose to describe the ECG as a superposition of cosinusoide functions weighted by Gaussian masking functions, each masking function being centered approximately around each of its corresponding wave (P, QRS, T).

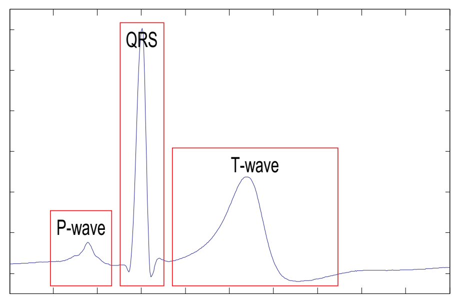

Figure 1: P, QRS and T wave of an ECG cycle

We found that the same model applies for each of the three waves, but the parameters of especially the Gaussian masking function differ a lot.

The proposed model is of the form

$$x(t) = \sum_{n=1}^{3} e^{\left(-\frac{t-t_{1n}}{T_n}\right)^2} \sum_{k=0}^{K} a_{nk} \cos(k\omega_n(t-t_{2n})) \;+\; O(t) \tag{1}$$

In that model, $n=1$ is related to the P wave, $n=2$ to the QRS wave while $n=3$ is related to the T wave. K is the number of harmonics needed, from experiments, $K = 2\ldots3$ was found to be sufficient.

In the context of this model, it makes no sense to distinguish a Q, R and S wave, as is done frequently in ECG interpretation. Instead, all three belong to the same term of the model ($n=2$).

Instead of the cosinusoides used here other orthogonal series expansions can be considered [11, 12], however, it can be expected that the frequency ω_n has an interpretable meaning that other approximations can not provide.

The model was tested on a proprietary database. First, a beat detection was performed in order to identify the R-R intervals. Second, an optimization in terms of the least square error was used to fit the model parameters.

3 MODEL IDENTIFICATION

Starting from an initial guess of the parameters of a whole ECG cycle based of the location of the peaks and the 60%-points of the waves (Fig. 2)

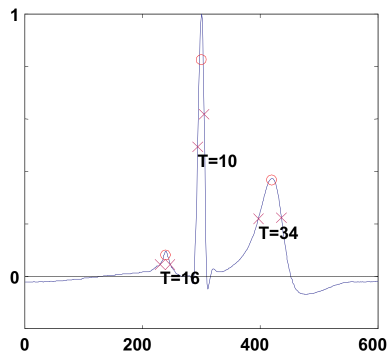

Figure 2: Peaks and 60%-points (for initial guess)

all parameters are identified simultaneously using a conventional Levenberg-Marquand procedure.

Given $\underline{\theta}$ being the vector of the model's 1 parameters

$$\underline{\theta} = [t_1 n, t_2 n, \omega_n, T_n, a_{nk}, k = 0 \ldots K, n = 1 \ldots 3] \quad (2)$$

let us define as $F(\underline{\theta})$ the approximation error vector and the associated LMS error $C(\underline{\theta})$ such that

$$F(\underline{\theta}) = [x_{\underline{\theta}}(n\Delta T) - d(n\Delta T), n = 1 \ldots L]^T \quad (3)$$

$$C(\underline{\theta}) = \|F(\underline{\theta})\|^2 \quad (4)$$

where $\Delta T = 1/f_s$ is the sampling period of the ECG signal $d(t)$ we want to approximate. For finding a vector $\hat{\underline{\theta}}$ that minimizes $C(\underline{\theta})$ (4), a modified quasi-Newton method (Levenberg-Marquardt) is used, providing a recursive estimate

$$\hat{\underline{\theta}}(k) = \hat{\underline{\theta}}(k-1) - [\underline{J}^T(k)\underline{J}(k) + \lambda_k I]^{-1}\underline{J}(k) \quad (5)$$

which converges towards a local minimum of $C(\underline{\theta})$, $\underline{J}(k)$ is the Jacobian matrix of $F(\underline{\theta})$ and λ_k biases the direction of the descent towards the gradient, making the procedure more robust than a Gauss-Newton method. For more details of the implementation, see [14].

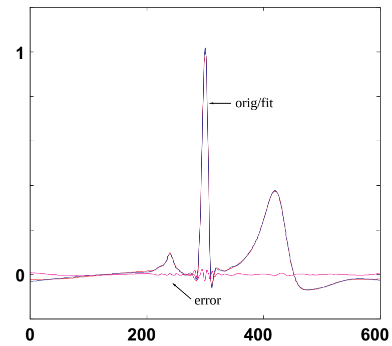

Figure 3: Original, fit and error of an entire cycle

For the next ECG cycle, the last set of parameters is used as a starting point of the optimization.

Figure 3 shows one typical result of curve fitting using the proposed model.

The quality of the fit is very high, the original waveform and the one obtained using the proposed model are hardly distinguishable. Note that due to the chosen harmonic series model (Eq. 1) for the modulation term, the error waveform has a cosinusoidal shape. A better insight on the model's approximation quality can be gained from the magnified view of the separate waves in Fig. 4,5,6.

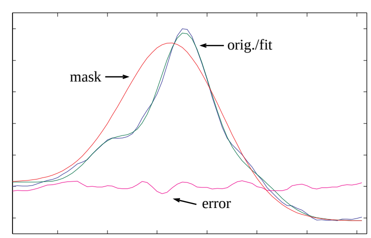

Figure 4: Orig., fit, error and mask (P wave)

Note that the relative error is larger for the P wave since it's amplitude is small compared to the QRS's. The baseline shift in Fig. 4 is due to the overlap of the models for the three waves.

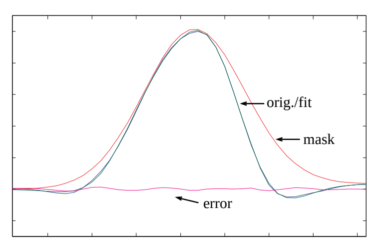

Figure 5: Orig., fit, error and mask (QRS wave)

The QRS wave (Fig. 5) presents the main motivation for the proposed model. Especially here it was found that only a Gaussian masking function is strong enough to follow exactly the well-defined onset and end of the QRS. Similar results have been found in [12].

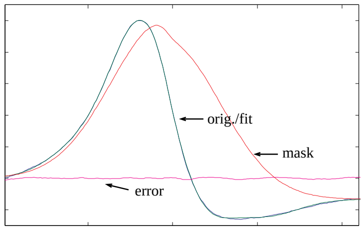

Figure 6: Orig., fit, error and mask (T wave)

Here the performance of the model is shown on noise-reduced ECG data (Fig. 1,2,3), but tests on more noisy (untreated) ECG show similar results, in fact the coding of the ECG using the model also introduces a noise reduction.

At this point, the optimization technique used is far from optimal. The *Matlab* optimization toolbox we used so far is sufficient for the model verification, but for a (desirably real time) implementation, an efficient adaptive algorithm needs to be devised.

This algorithm should certainly take into account the orthogonality of the modulation term's coefficients and should possibly employ a step-by-step technique by finding a raw model first and refining the model by adding higher harmonics later.

4 MODEL PERFORMANCE

Traditionally, the performance of an ECG compression scheme is evaluated by looking at the PRD (percent root mean square distortion) as defined in Eq. 6.

$$PRD = 100 \cdot \sqrt{\frac{\sum_{i=1}^{n} \left[x(i) - \hat{x}(i)\right]^2}{\sum_{i=1}^{n} x^2(i)}} \tag{6}$$

However, this error measure is only one aspect and must be considered side by side with feature conservation properties of the compression scheme [1]. Specifically, due to the great deviations of the signal's amplitude and scaling in time, it is clear that a simple distortion measure as the PRD can not characterize the performance sufficiently. In the literature [1], additionally, visual inspection by experienced persons is suggested.

The data compression capabilities of any modeling based scheme depend upon the number of parameters to be stored and their quantization. For the model proposed here the number of parameters is

$$N_{par} = 3 * (2 + 3 * K) + 3 = 36 \tag{7}$$

for the case of $K = 2$, which allows a high fidelity of the ECG reconstruction. Thus, using fixed point approximated parameters, the achieved compression ratio is about 15 to 16 for the 500 Hz sampling rate we used. These results are close to the state-of-the-art results obtained with adaptive Hermite polynomial and Karhunen-Loeve transforms. Additionally it is almost certain that the slow parameter variation from beat to beat can be exploited to both reduce the computational effort and increase the compression ratio.

The small beat to beat variations of the ECG's shape are not at all exploited (or only to a small extend) by traditional methods [1]. Herein lies one of the main advantages of the proposed model, that is a well-defined reproducible parameterization which can exploit the beat to beat similarities found in ECG data.

For comparing this method's performance, see Table 1 (after [1]). Due to the similarity of the approach, an overall performance of the presented method similar or better than that of the adaptive Hermite functions [11] is expected to be achievable. Of course, our technique needs to be optimized for use in compression.

Method	CR	f_s Hz	PRD (%)	Comments
AZTEC	10.0	500	28.0	Poor P and T fidelity
TP	2.0	200	5.3	Sensitive to Sampl. rate
CORTES	4.8	200	7.0	Poor P fidelity
SAPA	3.0	250	4.0	High fidelity
Entropy Coding	2.8	250	-	
DPCM Lin Pred	2.5	250	-	High fidelity
DPCM Lin Pred + Entropy cod.	7.8	500	3.5	High fidelity
Karhunen-Loeve	12.0	250	-	
Adapt. Hermite Functions	11.6	360	-	info on ectopic beat

Table 1: Comparison of ECG data compression schemes

5 CONCLUSION

The paper we present here shows that a very low-dimensional dynamical system can model the ECG signal. The main emphasis on this work lies on a new time-domain model accounting for the ECG dynamics. This model was shown to be tractable and to provide compression performances in the range of the state-of-the-art methods. Additional simulations will be carried out using the MIT-BIH database. The main characteristics of the model are as follows:

- The model provides a modelisation of the R-R interval without any help of a pre-segmentation algorithm inside the R-R interval.
- The complexity of the model is low with respect to the number of samples of the R-R interval, therefore

the model can be used for compression purpose.

- The model can implicitly detect the different waves inside the R-R interval since the optimization fitting procedure locate the Gaussian approximately at the center of the different waves (P, QRS, T).
- Some of the parameters as the Gaussian spreading T_{1n} have already a meaningful significance in terms of detection of ectopic beats (beat which have a duration greater than normal beats), we expect that the frequency terms in the modulated cosines provide also interesting signatures in terms of dynamical behavior of the cardio-vascular system.

The approach using a Gaussian masking function is similar to the work in [11, 12], even though there the notion of a masking function is not used. Here we use the same type of model for all three waves of the ECG, whereas [11] applies it to the QRS only. The main difference to the approach presented there is the use of a different orthonormal basis (Hermitian polynomes) whereas here a harmonic series is used.

From an approximation point of view this may seem of little difference, however from a dynamical point of view the harmonic series is more convenient since a strongly pronounced base frequency ω_n can be identified. This gives rise to the interesting question if the modulation can be modeled by a oscillator of frequency ω_n which contains a nonlinearity that produces higher harmonics. This aspect makes the presented model interesting for further research in the direction of an oscillator model for the ECG.

Currently an implementation on a TMS320C3x series DSP is in development, which will allow us to further investigate the real time performance of the parameter approximation.

Concluding we would like to stress that a low-dimensional nonlinear model explaining the ECG dynamics, suitable for data compression and possibly feature detection, has been developed. Using several tests on real clinically measured ECG signals we confirmed very good performance of the model in terms of small modeling errors.

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