Adaptive Hermite Models for ECG Data Compression: Performance and Evaluation with Automatic Wave Detection

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Abstract

An orthogonal transformation based on Hermite functions is proposed as a method for ECG data compression. In order to apply the procedure four signal windows are selected in each beat, corresponding to the principal ECG features: P wave, QRS complex, ST segment and T wave. The performance of the method is analysed calculating the compression ratio (CR) and the relative mean-square error (MSE) in each window and in the whole beat. The method has been applied to ECG records from MIT/BIH arrhytmia database. In normal beats with a CR=11.6, we have obtained a MSE = (0.09 ± 0.02) %. In ECG signals containing normal beats and multiform PVCs a MSE = (0.56 ± 3.41) % is obtained, with a CR=10.3. To analyse the clinical applicability of the method, the algorithm was evaluated with an automatic wave detection program. Differences between the automatic measures in the original signal and in the reconstructed signal were compared, and shown a good agreement.

1. Introduction

The great amount of data obtained when recording ECG signals necessitates data compression techniques for storing, transmitting and analysing the data, without loss of clinical information. In general, data compression techniques can be classified into three major groups: a) direct data compression, b) transformation using orthogonal functions, and c) parameter extraction. The most used techniques for ECG signals concern with the two first ones [1], because they are reversible processes that permit a subsequent reconstruction of the signal for later analysis and diagnosis.

In this study we propose a method for ECG data compression that is based on an orthogonal transformation using Hermite functions. This method was first used in [2] for evaluation of QRS shape features. It is based on calculating the inner product between the QRS complex and each Hermite function. The resulting coefficients represent the QRS shape and the width parameter b determines the width of the Gaussian in Hermite functions. Subsequently, we proposed in [3] an adaptive estimation system for calculating these coefficients in each beat of a real ECG sequence, attenuating noise not correlated with the signal.

In this work we study the potential of this method for ECG data compression. In order to apply the procedure to the signal, four windows have been selected in each beat, corresponding to the principal ECG features: P wave, QRS complex, ST segment and T wave. Each signal window is represented by an Hermite model to compress the ECG signal. We have applied this method to ECG records from the MIT/BIH Arrhythmia database, which include several types of beats: normal sinus, depression of ST segment, multiform PVCs and fusion beats.

The performance of the method was analysed calculating the compression ratio (CR) and the mean-square error (MSE) in each wave window and in the whole beat. Besides, in order to study the clinical applicability of the method, we have studied the boundary measurements of the ECG waves in the original and reconstructed data of the same record, by means of an automatic program [4].

2. The Hermite model

ECG signal waves can be represented by a set of orthogonal Hermite functions, with a finite number of parameters. These functions have the expression:

$$\Phi_n(t,b) = \frac{1}{\sqrt{b2^n n!\sqrt{\pi}}} e^{-\frac{t^2}{2b^2}} H_n(t/b) \qquad (1)$$

where $H_n(t/b)$ are the Hermite polynomials, and parameter b determines the temporal width of the

Hermite functions.

A previous study [5] shown the appropriateness of the Hermite model to represent the principal waves of the ECG signal (P, QRS, T) for data compression purposes. Subsequent analysis of performance made evident the need of modeling the ST segment, due to its importance in clinical diagnosis. In this way the approximated ECG features (P, QRS, ST, T) can be expressed as a linear combination of $\Phi_n(t,b)$:

$$\begin{Bmatrix} \mathrm{P(t)} \\ \mathrm{QRS(t)} \\ \mathrm{ST(t)} \\ \mathrm{T(t)} \end{Bmatrix} \simeq \begin{Bmatrix} \sum_{n=0}^{M_P-1} w_n^P(b_P)\Phi_n(t,b_P) \\ \sum_{n=0}^{M_{QRS}-1} w_n^{QRS}(b_{QRS})\Phi_n(t,b_{QRS}) \\ \sum_{n=0}^{M_{ST}-1} w_n^{ST}(b_{ST})\Phi_n(t,b_{ST}) \\ \sum_{n=0}^{M_T-1} w_n^T(b_T)\Phi_n(t,b_T) \end{Bmatrix} \quad (2)$$

where each feature i (= P, QRS, ST, T) is characterized by M_i+1 parameters: the M_i coefficients w_n^i, and the parameter b_i.

We proposed an adaptive system [3] for estimating these parameters, that is based on the multiple-input adaptive linear combiner. In this way, we have an estimation of the weights w_n^i as the inner product of the deterministic component of the signal and the $\Phi_n(t,b_i)$ functions, attenuating the effect of uncorrelated noise.

3. Preprocessing

In order to model the ECG signal, with the Hermite functions, several preprocessing steps must be applied: QRS detection and waves boundary detection, baseline wander removing, and linear approximation.

The first step consists of the QRS detection for beat identification. Next, the onset and offset of the most significant waves of ECG signal (P, QRS and T) are detected according to the method described in [6]. Baseline wander was removed by means of cubic splines approximation.

Once these steps are applied, four windows for each beat are defined: P wave, QRS complex, ST segment and T wave (fig. 1). Therefore, this method requires 6 parameters for each beat to define the four windows . After that, these signals can be represented by Hermite models. In order to obtain a good approximation, the Hermite model requires that the signal goes to zero at the onset and offset of the window. To achieve this, a linear trend removal is performed in each window. This information may be of clinical interest and it is saved for later signal reconstruction. Thus, in this step another 6 parameters are required for each beat.

4. Data compression performance

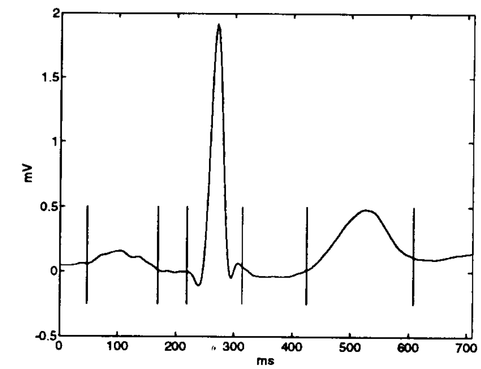

Figure 1: Wave onset and offset determination for signal window definition.

After the preprocessing, each signal window is represented by an Hermite model to compress the ECG signal using the method described in section 2. The performance of the method was analysed calculating the compression ratio (CR) and the relative mean-square error in each wave (MSE_w) and in the whole beat (MSE_{beat}). These indexes are defined as

$$CR = \frac{number\ of\ samples\ of\ X(n)}{number\ of\ parameters\ for\ Y(n)} \quad (3)$$

$$MSE_w = \frac{\sum_{n=1}^{N_w}[X(n)-Y(n)]^2}{\sum_{n=1}^{N_{beat}} X(n)^2} \quad (4)$$

where $X(n)$ is the original ECG signal, $Y(n)$ the reconstructed signal, N_w is the number of samples in the w window and N_{beat} is the whole beat samples.

The MSE index was selected instead of the most frequently used "percentile root mean square difference" (PRD), because it permits a separated analysis of different signal windows. Thus, we define the MSE_{beat}

$$MSE_{beat} = \sum_{w=1}^{M} MSE_w \quad (5)$$

where MSE_w is the relative mean-square error corresponding to window w.

According to the previous results of ECG data compression with Hermite models [5], the following parameters have been considered

Table 1: Parameters for ECG Data Compression

Signal processing step	P	QRS	ST	T	Beat
Boundary measurement	2	2	0	2	6
Linear approximation	2	2	0	2	6
Hermite modeling	2	7	2	4	15
TOTAL PARAMETERS	6	11	2	8	27

By other hand, the PR segment was reconstructed by a linear approximation, in order to complete the beat representation.

We have applied this method to ECG records from the MIT/BIH Arrhythmia database, which include several types of beats: normal sinus, depression of ST segment, multiform PVCs and fusion beats. These signals were sampled at $f_{samp} = 360$ Hz.

Using the parameters shown in table 1, we obtained for the records 103, 213, 215 and 221 (fig. 2) the values of CR and MSE shown in tables 2 and 3. We analyse the MSE in each wave and in the whole beat, for several sequences of the ECG signals with a duration of 100 seconds. In figure 3 we can see beats of the corresponding ECG signals reconstructed by this data compression method.

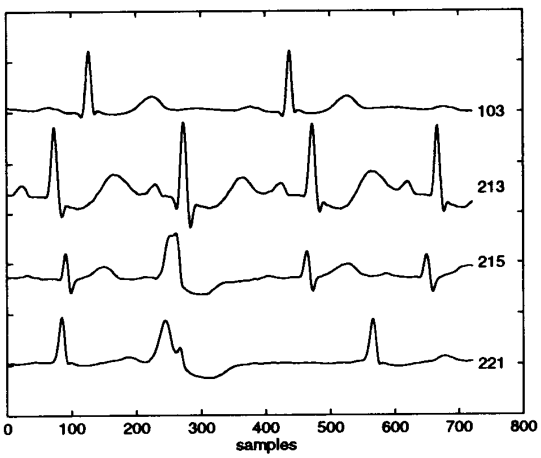

Figure 2: ECG records from the MIT/BIH arrhythmia database:103, 213, 215 and 221.

Table 2: CR and MSE_{beat} for ECG

ECG signal	# of beats	CR	MSE_{beat} $*10^2$
103	115	11.59	$\mu = .094$ $\sigma = .016$
213	181	7.37	$\mu = .198$ $\sigma = .069$
215	184	7.24	$\mu = .575$ $\sigma = 2.754$
221	129	10.33	$\mu = .560$ $\sigma = 3.408$

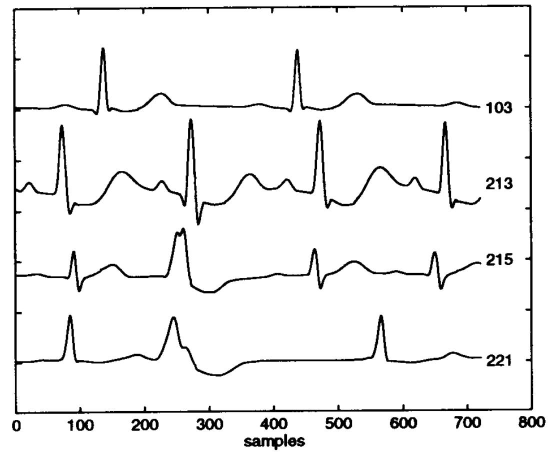

Figure 3: Reconstruction by Hermite models of ECG records from the MIT/BIH arrhythmia database:103, 213, 215 and 221.

Table 3: CR and MSE_w for ECG waves

ECG signal		$MSE * 10^2$ P	PR	QRS	ST	T
103	μ	.024	.016	.019	.024	.011
	σ	.007	.007	.007	.008	.006
213	μ	.031	.032	.017	.008	.110
	σ	.018	.015	.006	.006	.006
215	μ	.085	.305	.106	.005	.101
	σ	.346	2.322	.889	.009	.096
221	μ	.047	.143	.407	.035	.039
	σ	.149	.680	3.313	.037	.055

5. Automatic evaluation

The majority of authors use the error indexes as an objective method to analyse the performance of data compression methods. But in this way the impact on cardiological diagnosis is not evaluated. Other studies propose the analysis of onset and offset of the waves on the reconstructed signal [7].

In order to study the clinical applicability of the method we have studied the boundary measurements of the waves in the original and reconstructed data of the same record, by means of an automatic program [4,6] validated previously with the CSE database. The evaluation has been carried out in terms of the mean (μ) and standard deviation (σ) of the differences between: the automatic measurement in the original signal and in the reconstructed signal after data compression by Hermite models. In the table 4 we show the evaluation results. In order to analyse the goodness of the results we reproduced in table 5 the accepted tolerance for referee deviations, when measuring onset and offset of ECG waves [8].

We can conclude that the results corresponding to records 103, 213 and 215 achieve standard deviation values that are within the expert tolerance limits. These ECG signals includes ST depression, normal and fusion beats and multiform PVCs. The statistical results for record 221 surpass the referee values due to inaccurate modeling of very small number of PVCs on the complete sequence of beats.

Table 4: Original - Reconstructed Signal Boundaries

ECG	ms	P_{on}	P_{off}	QRS_{on}	QRS_{off}	T_{off}
103	μ	-2.92	-6.11	2.90	9.66	1.13
	σ	3.18	12.75	1.62	4.70	2.67
213	μ	-2.16	-0.63	2.79	-2.55	-5.22
	σ	1.98	1.92	2.13	1.55	3.02
215	μ	-1.86	1.86	1.97	-2.73	-1.60
	σ	4.47	11.80	8.32	7.30	20.02
221	μ	0.86	1.34	1.76	0.32	-6.68
	σ	11.49	7.48	16.23	12.28	64.07

Table 5: Accepted tolerances for referee deviations [8]

ms	P_{on}	P_{off}	QRS_{on}	QRS_{off}	T_{off}
σ_{ref}	10.2	12.7	6.5	11.6	30.6

6. Conclusions

Hermite models have shown to be very appropriated for ECG data compression. The application of powerful preprocessing steps has permitted a good reconstruction of the signal with a reduced number of parameters (27 for each beat).

The performance of the method has been analysed with the study of the compression ratio (CR) and the mean square error (MSE) for each wave of the ECG and for the whole beat.

The application of the method to ECG signals from MIT/BIH Arrhytmia database of different morphologies (including normal sinus beats, depression of ST segment, multiform PVCs and fusion beats) has shown a performance of MSE = (0.09 ± 0.02) % for normal beats (CR=11.6) and a MSE = (0.56 ± 3.41) % for ECG signals containing normal beats and multiform PVCs (CR=10.3).

Evaluation with automatic wave detection have confirmed the clinical applicability of the method, given that the results are within the acceptable tolerance of experts [8]. Further studies for a more extensive validation of the method would be necessary.

Acknowledgements

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