Compression and Analysis of ECG Features Using Optimal Polynomial Approximations

Daniel Tchiotsop, Valérie Louis Dorr, Pierre Kisito Talla, Médard Fogué

***Abstract*-- The electrocardiogram (ECG) is a signal reflecting the electrical activity of the heart muscles. Computer processing of ECG signals has been a very active area of research for decades. All modern recording systems of ECG incorporate compression software, automatic analysis and a guide for interpretation of the signal. The ECG signal is usually modeled by descriptors to facilitate the automatic analysis. We have proposed in this work, the modeling of the characteristic waves of ECG signal by the low degree polynomials, prior to compression and automatic analysis. To this end, we have implemented a complex QRS detection algorithm, and the extraction of the characteristics wave or intervals is carried out semi-automatically. Each segment of the extracted signal is then approximated by polynomials of low degrees, so that the error between the original signal and the approximation polynomial is minimum. Compression consists in keeping a small number of polynomial coefficients to store or transmit the signal, instead of the large amount of samples values. We have obtained very satisfactory results as regards the compression with very high compression ratio and low values of PRD (Percent Difference square root). We have also shown that the coefficients from the polynomial approximations can be used for the automatic analysis of the signal, especially in the estimation of peak values of the waves and determining their concavities. It is possible to establish correlations between the coefficients of the polynomial approximation and the energy of the signal, and also the spectral congestion of the signal. Similarly, tools of intelligent systems such as artificial neural networks and fuzzy logic may be associated with the polynomial coefficients for the automatic interpretation of the ECG signal.**

***Index Terms*— Automated Analysis of ECG, Compression of ECG, ECG Features extraction, Optimal polynomial approximations.**

I. INTRODUCTION

The electrocardiogram (ECG) is a typical tracing reflecting the heart electrical activities. ECG is an essential tool in medicine, to determine the character of certain heart disorders. Modern ECG recorders provide an automatic analysis of registered signals that performs partial diagnosis. Computer analysis of ECG is essential for cardiologists in both emergency situations where the diagnosis must be made in minutes, and to help producing reports from a vast amount of ECG data, such as holter system recorded and store on tape in 24 hours, resulting as 100, 000 beats/channel [1], [2], [3], [4], [5].

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Dr Daniel Tchiotsop, Department of Electrical Engineering, IUT FV University of Dschang – Cameroon
Pr Valérie Louis Dorr, CRAN UMR CNRS 7039, ENSEM Université de Lorraine, Nancy, France
Pr Pierre Kisito Talla, Department of Physics, Faculty of Science, University of Dschang – Cameroon
Pr Médard Fogué, Department of Mechanical Engineering, IUT FV, University of Dschang - Cameroon

An exhaustive review of algorithms proposed in literature for extraction and classification of ECG features can be found in [6]. Particular attention is given to the QRS complexes that are commonly regarded as the most important waves. The methods used for QRS classification can been divided in two categories: template matching and features extraction/classification. In the "template matching" approach, QRS are represented by time series samples. QRS similarity comparisons are performed by means of either cross-correlation or area differences computations [7], [8]. In the feature extraction/classification approach, QRS are represented by a set of descriptors such as coefficients of an orthogonal vectors set. Features are considered to represent each QRS as a point in a space. The similarity measurements are defined as distance separating these points [**9**], [10]
Hermite functions have been intensively used for morphological modelling of QRS complexes before classification. A pioneer idea for such QRS modelling was presented in [11] at the early 80's, where a three dimensional space for QRS morphologies, using the first three Hermite functions as the basic vectors was elaborated. The authors constructed a mathematical norm to measure QRS shapes as they observed that the three first Hermite functions have similar morphologies respectively as mono-phasic, bi-phasic and tri-phasic QRS. In [12], the first six Hermite functions were used to represent QRS complexes, an adaptive classification scheme was next applied to the models. Many other modelling of QRS complexes parameters through Hermite functions are studied in [13]. The classification schemes are achieved by a Self Organization Map (MOP), Atificial Neural Network (ANN) and Fuzzy logic. [14], [15], [16], [17].

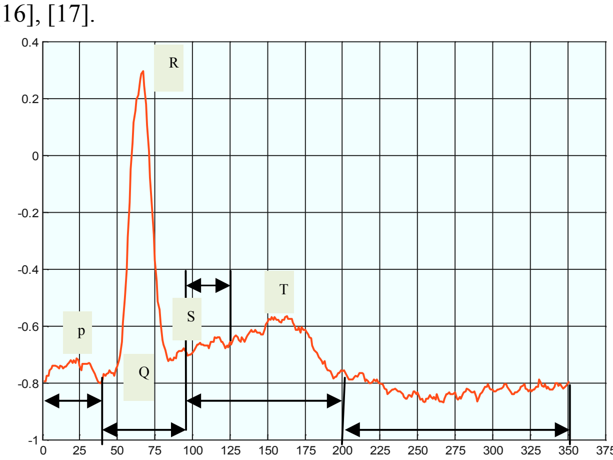

Figure1: ECG waves and intervals. The double arrows indicate from left to right: P-R interval, QRS interval, S-T segment, S-T interval and T-P segment.

Although most computerized classification methods for ECG focus on the QRS complexes, the other waves and intervals of the ECG also hold important medical information. Various waves and intervals of an ECG signal are shown in figure 1. It is therefore necessary to classify automatically the parameters of these waves and intervals in order to facilitate evaluation by the cardiologist. We propose in this paper, a semi-automatic extraction of ECG features, the optimal polynomial mapping of these features by low degrees polynomials. Some applications for compression and for automated ECG analysis are carried out. The idea of representing ECG segments by second degree polynomials was first introduced in [18]. For this matter, some specific points of ECG were detected and used as nodes for second degree polynomial interpolation. Our strategy is quite different from this since we do extract the waves and the intervals to reach significant medical information and the modelling is more accurate using optimal polynomial approximations. Some more elaborated schemes for ECG data compression using high degree orthogonal polynomials has been carried on in our previous studies [19], [20] and [21]. In the above mentioned studies, orthogonal polynomials such as Chebyshev polynomials, Legendre polynomials, generalized Jacobi polynomials, Laguerre polynomials and Hermite polynomials are used as basic functions for the decomposition of ECG signals.

The remainder of this paper is organized as follows: in the next section we revisit the theory of best polynomial approximations to emphasize the principle of optimal polynomial approximation. Section III is devoted to the process of ECG's waves and intervals extraction. The results of compression and automated computerized analysis of ECG using the optimal polynomial approximations are presented and discussed in section IV. A conclusion ends the paper.

II. SURVEY ON OPTIMAL POLYNOMIAL APPROXIMATION THEORY

A. General concept

Let's consider a continuous signal $s(t)$, that can be approximated by a set of polynomials $P=\{p_0(t),\quad p_1(t),\quad \dots\quad p_n(t)\}$ such that

$$\hat{s}(t)\quad \sum_{k=0}^{n} a_k p_k(t) \tag{1}$$

The approximation is optimal if the error between the signal $s(t)$ and its polynomial approximation $\hat{s}(t)$ is minimal.

One approach to evaluate the error E between $s(t)$ and its approximation is to consider the metric distance $d\left(s(t),\hat{s}(t)\right)$ between the two signals in a metric space.

Since the metric distance is related to a given norm and the norm is defined from the inner product, we have:

$$d(\mathbf{s},\hat{\mathbf{s}}) = E = \left\| \mathbf{s} - \sum_{k=0}^{n} a_k \mathbf{p}_k \right\| \tag{2}$$

The problem of optimal polynomial approximation of a signal can then be formulated as follows:

$$\min d(\mathbf{s},\hat{\mathbf{s}}) \quad \text{or} \quad \min E \tag{3}$$

where

$$E^2 = \left\langle \mathbf{s} - \sum_{k=0}^{n} a_k \mathbf{p}_k \ ,\ \mathbf{s} - \sum_{k=0}^{n} a_k \mathbf{p}_k \right\rangle = \left\| \mathbf{s} - \sum_{k=0}^{n} a_k \mathbf{p}_k \right\|^2$$

The choice of a given norm specifies the optimal polynomial method. The Least Square polynomial fitting uses a norm derived from the inner product defined in $L^2[a,b]$ as

$\langle \mathbf{u},\mathbf{v}\rangle = \int_a^b u(x)v(x)dx$, thus

$$\|u(t)\| = \sqrt{\int_a^b (u(t))^2 dt} \tag{4}$$

Minimax polynomial approximation is also a special case of such optimal polynomial approximation where the infinity norm is used: $\|s(t)\|_\infty = \max_{t\in]a,b[} |(s(t))|$. (5)

B- The least square approximation

Suppose that the polynomial q(t) used to approximate s(t) in the time interval $[t_1\ ,t_2]$ is of degree at most n such that:

$$q(t) = a_0 + a_1 t + \quad \dots \quad + a_n t = \sum_{k=0}^{n} a_k t^k \tag{6}$$

The least square approximation consists in minimizing the error E^2 is defined as:

$$E^2(a_0,a_1,\quad \dots \quad ,a_n) = \int_{t_1}^{t_2} \left[s(t) - \sum_{k=0}^{n} a_k t^k \right]^2 dt \tag{7}$$

We then have to find coefficients $a_0,a_1,\quad \dots \quad ,a_n$ such that

$$\frac{\partial E^2}{\partial a_j} = 0 \ \text{ for } \ j = 0,1,\quad \dots \quad ,n. \tag{8}$$

We can rewrite E as follows:

$$E^2 = \int_{t_1}^{t_2} [s(t)]^2 dt - 2\sum_{k=0}^{n} a_k \int_{t_1}^{t_2} t^k s(t)dt + \int_{t_1}^{t_2} \left[\sum_{k=0}^{n} a_k t^k \right]^2 dt \tag{9}$$

It then comes that:

$$\frac{\partial E^2}{\partial a_j} = -2\int_{t_1}^{t_2} t^j s(t)dt + 2\sum_{k=0}^{n} a_k \int_{t_1}^{t_2} t^{k+j} dt \tag{10}$$

Thus $\frac{\partial E^2}{\partial a_j} = 0$ becomes

$$\int_{t_1}^{t_2} t^j s(t)dt = \sum_{k=0}^{n} a_k \int_{t_1}^{t_2} t^{k+j} dt \tag{11}$$

To find the polynomial q(t), we need to solve a system of (n+1) linear equations having (n+1) unknowns: $a_0,a_1,\quad \dots \quad ,a_n$.

When dealing with a sequence of discrete signal $\{y_i\}$, equation (7) becomes (12):

$$E^2(a_0,a_1,\quad \dots \quad ,a_n) = \sum_{i=1}^{m} \left(y_i - \sum_{j=0}^{n} a_j t_i^j \right)^2 \tag{12}$$

The equation (8) then leads to (13).

$$\begin{pmatrix} \sum_{i=1}^{m} 1 & \sum_{i=1}^{m} t_i & & \sum_{i=1}^{m} t_i^n \\ \sum_{i=1}^{m} t_i & \sum_{i=1}^{m} t_i^2 & \dots & \sum_{i=1}^{m} t_i^{n+1} \\ & & & \\ \sum_{i=1}^{m} t_i^n & \sum_{i=1}^{m} t_i^{n+1} & & \sum_{i=1}^{m} t_i^{2n} \end{pmatrix} \begin{pmatrix} a_0 \\ . \\ . \\ . \\ a_n \end{pmatrix} = \begin{pmatrix} \sum_{i=1}^{m} y_i \\ \sum_{i=1}^{m} t_i y_i \\ . \\ . \\ \sum_{i=1}^{m} t_i^n y_i \end{pmatrix} \quad (13)$$

If we adopt the following notation:

$$s_k = \sum_{i=1}^{m} t_i^k \qquad k = 0, 1, ..., 2n \qquad (14)$$

$$b_k = \sum_{i=1}^{m} t_i^k y_i \qquad k = 0, 1, ... ,n$$

Then to find the coefficients (a_0, a_1, ... , a_n) of the optimal polynomial approximation, we just have to solve the linear algebraic system

$$\mathbf{S.a = b} \qquad (15)$$

Where $\mathbf{S} = \begin{pmatrix} s_0 & s_1 & & s_n \\ s_1 & s_2 & & s_{n+1} \\ & & & \\ s_n & s_{n+1} & & s_{2n} \end{pmatrix}$ $\quad \mathbf{a} = \begin{pmatrix} a_0 \\ a_1 \\ \\ a_n \end{pmatrix}$

$\mathbf{b} = \begin{pmatrix} b_0 \\ b_1 \\ \\ b_n \end{pmatrix}$

III. MATERIAL AND METHODS

A. Bloc diagram

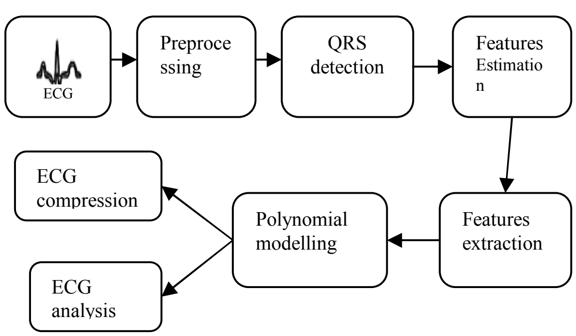

Figure 2: overall block diagram

The overall bloc diagram of the work presented in this paper is shown in figure 2. Some specific intervals of ECG are extracted from the input signals. These intervals are next approximated optimally by polynomials. The coefficients of polynomials can be used for automated analysis or to achieve compression. All specimens of signal used for simulations and tests in this work were down loaded from the free online data base PHYSIONET [22]. The Programs were implemented in the Matlab environment, using the version 2009 Rb.

B. Semi automatic waves detection and intervals extraction

A typical ECG tracing highlighting its various waves and intervals is shown in figure 1. Prior to best polynomial approximation, the concerned waves and intervals of ECGs should be correctly identified and extracted. The detection of QRS complexes is not a problem since many robust algorithms exist. In the other hand, the detection of P wave and the detection of the T wave are not obvious. Some solutions have been proposed for the detection of P and T waves, but they are not reliable enough and require very long computing time.

In addition to the waves' detection, the limits of these waves should be located in order to correctly estimate the intervals of the signal to be approximated by polynomials. A study on identifying the beginnings and the ends of the waves of the ECG signal has been done in [23]. We achieve the detection of QRS complex using a fast and very robust algorithm proposed in [24]. This algorithm enables detection of QRS complexes in five steps: Band pass filtering, signal differentiation, non linear amplification (squaring function), integration and adaptive threshold. An illustration of its operations is given in Figure 3.

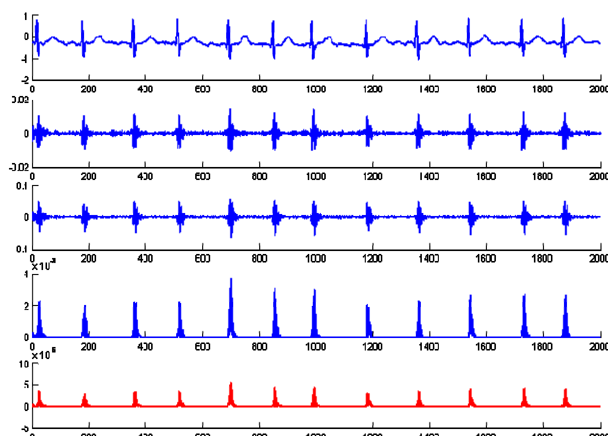

Figure 3: Illustration of the implementation of the different steps involved in QRS detection scheme [24].

The position provided by the QRS detector can match with the Q wave, with the R wave or with the S wave according to the morphology of the QRS complex. To determine the onsets and the offsets of the waves, we return to the stage of differentiation to scan the successive passages through zero, minimums and maximums . The information collected at this level are used to locate the correct Q, R, (possibly R ') and S waves. Although it is proposed in [23] to use the same procedure to identify the beginnings and endings of both P and T waves, we preferred to manually pick the onsets and offsets of P and T waves through the interactive graphical user interface of Matlab. Having the data gathered from onsets and offsets of various waves, any specific type of intervals could be easily extracted. In figure 4 is shown an example of ECG signal with the extracted P waves, QRS complexes and S waves.

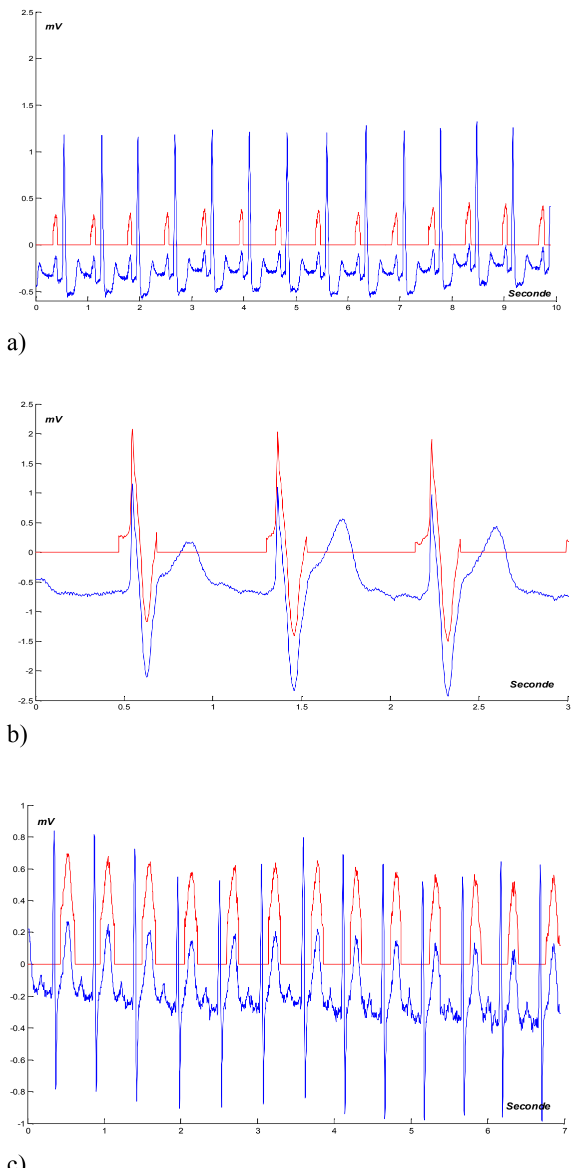

Figure 4: Examples of extracted waves: a) P waves extracted, b) QRS extracted and c) T waves extracted. P waves from record MIT105 of [22], QRS complexes from record MIT219 of [22] and T waves:from record 215 of [22].

C. The appraisal of the approximation quality

Visual inspection is the natural standard for the quality evaluation of the reconstructed signal through optimal polynomial approximation. This is as true as cardiologists who are the main users of ECG signals make diagnosis by visual inspection. In biomedical signal processing, some theoretical formulas are usually called upon to estimate the distortion rate between the original signal and its approximation. Among, these formulas, we will use:

- The Percent Root square Difference (PRD) expressed as follows:

$$PRD = \sqrt{\frac{\sum_n \left(s(n) - \hat{s}(n)\right)^2}{\sum_n \left(s(n)\right)^2}}.100 \quad \% \qquad (16)$$

where $s(n)$ and $\hat{s}(n)$ are original and reconstructed signals samples respectively.

- The Maximun Amplitude Deviation MADev

$$MADev = \max_{i=1\,to\,N} \left|s(i) - \hat{s}(i)\right| \qquad (17)$$

Where N is total number of samples in the signal. MADev is the discrete version of the norm $\|.\|_\infty$

- The mean square error MSErr

$$MSErr = \frac{1}{N}\sum_{i=1}^{N}\left|s(i) - \hat{s}(i)\right|^2 \qquad (18)$$

- The Standard Deviation StDev

$$StDev = \frac{1}{N}\sqrt{\sum_{i=1}^{N}\left(s(i) - \hat{s}(i)\right)^2 - \left[\sum_{i=1}^{N}\left(s(i) - \hat{s}(i)\right)\right]^2} \qquad (19)$$

The PRD and the MSErr are related to the energy distortion, the MADev concerns shape distortion while StDev gives information about statistics of error dispersion. The compression ratio (CR) is defined as the ratio between the number of bits used to store the original signal over the number of bits coding the compressed signal.

IV. Results, Applications and discussion

A. Efficiency of polynomial mapping of ECG waves

We used the Least square approximation algorithm scheme to estimate P waves, QRS complexes and T waves of hundreds of signals from the data bases incuded in[physion]. It can be seen in figure 5, figure 6 and figure 7 respectively, the approximations of P waves, QRS complexes and T waves, by polynomials of various degrees.

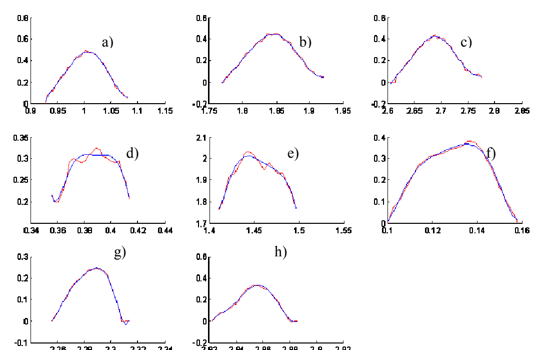

Figure 5: Optimal polynomial approximation of P waves using polynomials of degree 5. The original P wave signals are in red while their approximations are in blue.

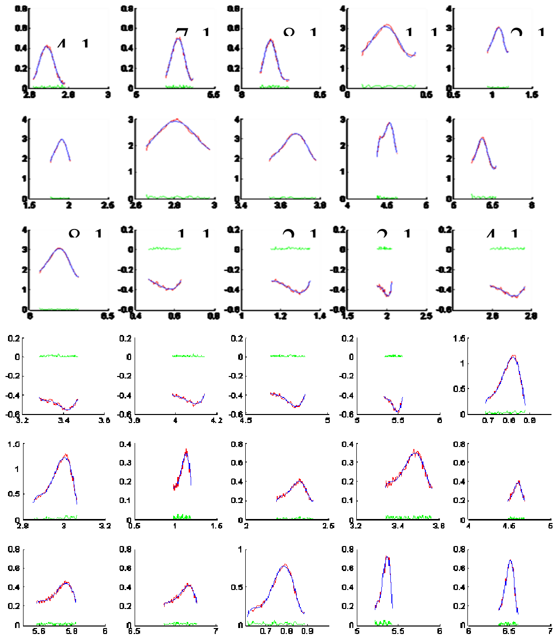

Figure 6: Polynomials models for T waves using degree 5 optimal polynomial approximations. The T waves are from the records 103, 107, 111, 113,114 and 117 [22]. The original signals are in red, the polynomial models are in blue and the green signals are the errors between the original and its approximation.

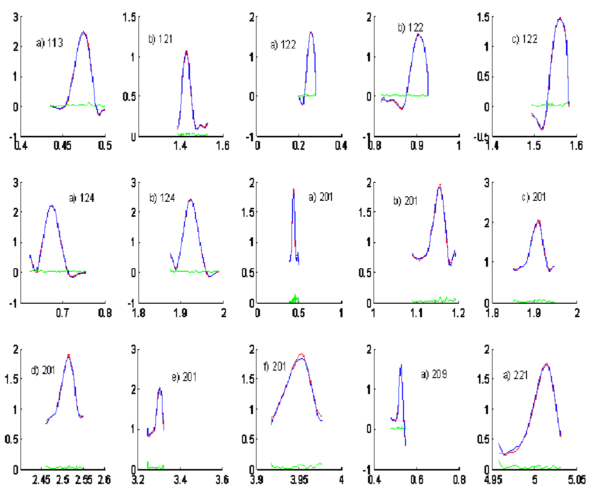

Figure 7: Polynomials models for QRS complexes using degree 8 optimal polynomial approximations. The QRS complexes are from the records 113, 121, 122, 124, 201, 209, and 221. of [22]. The original signals are in red, the polynomial models are in blue and the green signals are the errors between the original and its approximation.

B. Application for ECG data compression.
To achieve the compression of ECG signals, we begin by segmenting the signals into portions corresponding to the cardiac cycles. Each cardiac cycle is then divided into four zones: the PQ segment, the QRS complex, the ST interval and the TP segment. We apply polynomial approximation algorithms optimal on each of these signal segments. We then obtain polynomials whose coefficients can be stored or transmitted instead of the signal samples. The number of polynomials coefficients is very small compared to the number of samples of the signals. Compression is then achieved as small number of polynomials coefficients is used to represent the huge quantity of data of ECGs. Scalar quantization could next be applied to polynomials coefficients such that they are stored by computer systems as integers. Doing this increases the compression ratio. Further, entropic encodings such as run length encoding or Huffman encoding could be applied on the polynomial coefficients obtained in order to improve the compression ratio. Some results of compression are given in table 1. Polynomials of degree 5 are used to approximate the P-Q and S-T intervals while QRS complexes are mapped by polynomials of degree 8. No lossless compression scheme has been associated to optimal polynomial approximations. The compression ratios (CR) are thus the ratio of the number of samples in the signal intervals over the number of polynomial coefficients used to approximate that signal intervals. It comes from the values in table 1 that high compression ratios are achieved with very small PRD.

C. Application for ECG signal analysis

Most of the computerized ECG analysis are performed in time domain. Cardiologists need to measure the time durations of various waves and intervals to carry on diagnosis. When we do approximate ECG waves by low degrees polynomials, the time parameter is masked by the polynomial variable. Although it is possible to establish some correlation between the polynomial variable and the time parameter; this will not be so useful, rather, it adds complexities to the analysis process. Polynomial approximations are then no suitable for time domain analysis of ECG signals.

Nevertheless, there are many ECG signal analysis that focus on amplitude measures. For instance, the value of the amplitude of the P wave, the value of the amplitude of the R wave and the value of the amplitude of the T wave are essential information for the cardiologist. These values can be easily retrieved from ECG data using optimal polynomial approximations. For instance, if we consider the second degree polynomial approximations of the above waves, that is:

$$\begin{aligned} &P(x) = a_P x^2 + b_P x + c_P \text{ for P waves,} \\ &R(x) = a_R x^2 + b_R x + c_R \text{ for R waves,} \\ &T(x) = a_T x^2 + b_T x + c_T \text{ for T waves,} \end{aligned} \tag{20}$$

The extrema of such polynomials are obtained when their derivatives are equals to zero. These extrema are the peak maximum or the peak minimum values of the waves. It comes that:

$$\begin{aligned} &|P(x)|_{\max} = |-b_P/2a_P|, \quad |R(x)|_{\max} = |-b_R/2a_R|, \\ &|T(x)|_{\max} = |-b_T/2a_T| \end{aligned} \tag{21}$$

The maximal values of various waves are then calculated by using the second order polynomials coefficients.

The cardiologists also evaluate the directions of current flow into the heart electrical network by scrutinizing the concavity of various ECG waves. It is very easy to know the concavities of an ECG waves using its second degree polynomial model. For instance, if $a_P > 0$ then the P wave is negative and if $a_P < 0$, then the P wave is positive. The same, R wave and T wave are negative for positive a_R and a_T respectively, and R wave and T wave are positive for negative a_R and a_T. The determination of the concavity is direct and appears obvious when using polynomial approximations. It would have needed very long and complex algorithms in both the time domain and the frequency domain to arrive to such conclusions.

Table1: Results of polynomial compression of ECG intervals

Records	*ECG Intervals*	$(P\text{-}Q)_1$	$(QRS)_1$	$(S\text{-}T)_1$	$(P\text{-}Q)_2$	$(QRS)_2$	$(S\text{-}T)_2$	$(P\text{-}Q)_3$	$(QRQ)_3$	$(S\text{-}T)_3$
MIT_101	***MSErr(mv^2)***	0,11	0,01	0	0,04	0,43	0	0,13	0,08	0,01
	PRD(%)	**1,35**	**4,21**	**4,68**	**0,87**	**5,27**	**4,2**	**1,54**	**3,93**	**4,21**
	MADev (mV)	0,1	0,05	0,02	0,06	0,42	0,02	0,11	0,19	0,02
	CR	13.6	08.75	22.3	13.6	08.75	22.3	13.6	08.75	22.3
MIT_103	***MSErr(mv^2)***	0.003	0,06	0,01	0.005	0,02	0,01	0.006	0,1	0,01
	PRD(%)	**2.53**	**4,08**	**2,52**	**3.52**	**3,64**	**4,73**	**3.73**	**5,79**	**3,72**
	MADev (mV)	0.016	0,13	0,03	0.023	0,04	0,07	0.025	0,1	0,02
	CR	14.4	08.0	17.41	14.4	08.0	17.41	14.4	08.0	17.41
MIT_105	***MSErr(mv^2)***	0.00	0,05	0.00	0.01	0,02	0,01	0.011	0,03	0
	PRD(%)	**1.95**	**4,97**	**4,84**	**2.7**	**2,88**	**6,71**	**5.19**	**3,58**	**5,37**
	MADev (mV)	0.010	0,04	0,03	0.021	0,05	0,04	0.04	0,07	0,03
	CR	10.8	09.62	13.4	10.8	09.62	13.4	10.8	09.62	13.4
MIT_106	***MSErr(mv^2)***	0,01	0,01	0,02	0,01	0,05	0,04	0,01	0,39	0,02
	PRD(%)	**2,63**	**1,55**	**2,88**	**2,73**	**2,83**	**4,16**	**2,11**	**4,46**	**2,88**
	MADev (mV)	0,02	0,04	0,04	0,02	0,13	0,07	0,03	0,45	0,04
	CR	13.0	10.0	23.4	13.0	10.0	23.4	13.0	10.0	23.4
MIT_107	***MSErr(mv^2)***	0.004	0,1	0,03	0.43	0,05	0,02	0,01	0,04	0,01
	PRD(%)	**0.61**	**4,17**	**0,66**	**1.53**	**3,23**	**0,54**	**1,49**	**2,73**	**0,33**
	MADev (mV)	0.02	0,21	0,05	0.09	0,1	0,04	0,03	0,08	0,02
	CR	13.8	11.8	25.2	13.0	10.0	23.4	13.0	10.0	23.4
MIT_111	***MSErr(mv^2)***	0,01	0,3	0	0,01	0,15	0,01	0,01	0,25	0,01
	PRD(%)	**2,42**	**3,19**	**2,52**	**2,91**	**4,27**	**2,64**	**2,58**	**5,2**	**2,93**
	MADev (mV)	0,03	0,17	0,02	0,03	0,16	0,02	0,02	0,19	0,03
	CR	10.2	7.3	21.2	10.2	7.3	21.2	10.2	7.3	21.2
MIT_113	***MSErr(mv^2)***	0.00	0,02	0,01	0.002	0,11	0,02	0.016	0,11	0,02
	PRD(%)	**1.40**	**3,77**	**1,59**	**1.87**	**6,34**	**2,02**	**3.81**	**4,98**	**1,75**
	MADev (mV)	0.009	0,07	0,03	0.02	0,12	0,04	0.109	0,33	0,04
	CR	16.6	5.3	18.6	16.6	5.3	18.6	16.6	5.3	18.6
MIT_114	***MSErr(mv^2)***	0,21	0,01	0,01	0,13	0,06	0,01	0,32	0,26	0,01
	PRD(%)	**1,55**	**3,29**	**3,79**	**1,45**	**4,09**	**3,87**	**2,07**	**4,81**	**3,13**
	MADev (mV)	0,18	0,06	0,02	0,1	0,14	0,03	0,16	0,09	0,03
	CR	12.4	5.8	24.4	12.4	5.8	24.4	12.4	5.8	24.4

D. Discussion

The optimal polynomial approximation of functions is not new in mathematics. This technique has not gained the same benefit in signal processing as other mathematical modelling methods such as Fourier transform and wavelet transform. For ECG data compression, we have shown that if a correct strategy is adopted, one can performed efficient compression scheme using optimal polynomial approximation. The results could even be improved by involving lossless compression techniques to polynomials coefficients. In fact, different cardiac cycles of the same signal are quite similar and redundancy should arise in polynomial coefficients mapping the same wave in different cardiac cycles. We have also shown that the second order polynomial coefficients can be used to estimate the peak values of signal. It is easier to calculate de peak values using these coefficients than doing multiple comparisons of samples, or doing amplitude to time conversion and counting. The concavity assessment is a very easy task when using the polynomial coefficients. The optimal polynomial approximation of signal is then a precious tool for signal processing and further investigations should be considered on its applications.

Conclusion

The set objectives of this work were to model the characteristics waves and intervals ECG signal through optimal polynomial approximations, and use the resulting models to achieve compression and automatic analysis. These objectives have been largely achieved because we managed to achieve compression with compression ratio higher than 25 and the PRD lower 1 %. The coefficients from the polynomial approximations have been exploited to estimate peak values of waves and their concavities. We have shown that the theory of optimal polynomial approximations can have very interesting applications in signal processing. Some correlations between the polynomial coefficients and the energy of the signal, and also between the coefficients of the approximating polynomials and the bandwidth of the signal may be considered. One can also consider the application of heuristics techniques on these coefficients for the automatic interpretation of the ECG signal.

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Tchiotsop Daniel was born in 1965 in Tombel - Cameroon. He graduated in Electromechanical engineering from the Ecole Nationale Supérieure Polytechnique (ENSP) of Yaoundé-Cameroon in 1990, he obtained a MS degree in Solid Physics in 1992 from the Faculty of Science of the University of Yaoundé I, a MS degree in Electrical Engineering and Telecommunication in 2003 from ENSP-Yaoundé and a PHD at INPL (Institut National Polytechnique de Lorraine), Nancy–France, in 2007. Dr

TCHIOTSOP teaches in the Department of Electrical Engineering of the FOTSO Victor University Institute of Technology – University of Dschang since 1999 where he is actually the Head of Department. He is with the Laboratoire d'Automatique et d'Informatique Appliquée (LAIA) where his main items of research include Biomedical Engineering, Biomedical signal and image processing, Telemedicine and intelligent systems.

Valérie Louis Dorr is a Professor at the Research Center for Automatic Control (CRAN/CNRS) Lorraine University, Nancy, France. Since 1996 her field of research is signal processing and the analysis of physiological signals. Since 2000, her work has focused on EEG processing in an epileptic context. Her main interests are denoising, preprocessing and source separation, connectivity model

TALLA Pierre Kisito was born in 1959 at Bamendjou in Cameroon. He obtained various university titles as follow:
1983 : GC advanced level,
1986: BSc in Physics, Faculty of Sciences, University of Yaoundé
1989: MSc in Mechanics, University of Yaoundé.
1994: MPHil in Mechanics, Faculty of Sciences, University of Yaoundé
2008: PhD in Mechanics of intelligent materials, faculty of Sciences, university of Dschang,
Juin 1995 : Assistant Lecturer, Department of Physics, Faculty of Sciences, University of Dschang
Since November 1998 : Coordonnator of the Department of Physics, Faculty of Sciences, University of Dschang
Since february 2003 : Lecturer in the Department of Physics, Faculty of Sciences, University of Dschang
Since November 2005 : HOD, Department of Physics, Faculty of Sciences, University of Dschang
Since November 2010 : Associate Professor, Department of Physics, Faculty of Sciences, University of Dschang
.

Fogué Médard Was born in 1955 in Cameroon. He obtained High technical school teacher training certificate in 1979 at ENSET Douala. He was graduated a Mechanical Engineer and also obtained a Master of Science degree in mechanical construction engineering at INSA Lyon France in 1984. Pr. Médard Fogué obtained a PhD in 1987 in France and the HDR (Habilitation for Mastering Research) in 2000. From 1988 to 1999, he was senior lecturer and has been the Head of the Department of mechanical engineering at the National High School of Engineering (ENSP) of Yaoundé. Since 1999, he is the Director of FOTSO Victor University Institute of Technology of the University of Dschang. He is the Director of the Environmental and Industrial Systems Engineering Laboratory (LISIE) at FOTSO Victor University Institute of Technology. The main concerns of his research are Solid mechanics, Fatigue, Foundry, Materials, and Lifetime, software design for vibration of structures, non destructive control, Modeling, Reliability, and Maintenance.