Electrocardiogram reconstruction based on Hermite interpolating polynomial with Chebyshev nodes

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ABSTRACT

Electrocardiogram (ECG) signals generate massive volume of digital data, so they need to be suitably compressed for efficient transmission and storage. Polynomial approximations and polynomial interpolation have been used for ECG data compression where the data signal is described by polynomial coefficients only. Here, we propose approximation using hermite polynomial interpolation with chebyshev nodes for compressing ECG signals that consequently denoises them too. Recommended algorithm is applied on various ECG signals taken from MIT-BIH arrhythmia database without any additional noise as the signals are already contaminated with noise. Performance of the proposed algorithm is evaluated using various performance metrics and compared with some recent compression techniques. Experimental results prove that the proposed method efficiently compresses the ECG signals while preserving the minute details of important morphological features of ECG signal required for clinical diagnosis.

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1. INTRODUCTION

Electrocardiogram (ECG or EKG) is a recording of 1-D time series data sequence generated by cardiac muscles. They help to track and detect abnormalities in the heart rhythm based on the morphology and frequency of heartbeat [1]. 24 hours ECG record with the sampling rate of 360 Hz and 11 bit/sample data resolution requires about 43 MBytes per channel [2]. Therefore, an effective data compression scheme is often required for efficient ECG data storage and transmission over telephone line or digital telecommunication network [3]. ECG compression techniques can be broadly classified into three major categories: direct time domain, parameter extraction and transform domain method [4].

In direct time domain method compression is achieved by finding correlation between the adjacent samples, i.e., intra-beat redundancy in a group and encode them into a smaller sub-group [5]. Some popular algorithms of direct method are: amplitude zone time epoch coding (AZTECH) [6], coordinate reduction time encoding system (CORTES) [7], entropy coding [8], scan-along polygonal approximation (SAPA) [9] and long–term prediction (LTP) [10]. Parameter extraction methods extract important morphological features from the signal and encode these features to achieve desired compression [11], e.g., linear prediction [12] and residual encoding methods [13]. In transform domain method signals are transformed to another space using various transform schemes [14], in the subsequent steps small transform coefficients are discarded and only critical information is encoded to achieve the desired compression. Transform techniques include fourier transforms [15], discrete wavelet transform (DWT) [16], discrete cosine transform (DCT) [17], discrete Legendre transform [18] and Karhunen Louve transform (KLT) [19].

Polynomials find application in signal processing, viz., for filtering noisy signals, interpolating data sequence, and for data compression [20]. High compression ratio can be achieved by polynomial approximation, since, polynomial coefficients describing the signal are only required for compression [21]. Legendre polynomials is used by [22] for image compression and reconstruction. For higher order of polynomials the Vandermonde matrix gets ill conditioned which is avoided by dividing image matrix into sub-matrices to achieve desired compression ratio. ECG data compression utilizing Jacobi polynomials is proposed by [23]. ECG signals are first segmented into blocks that match with cardiac cycles before being decomposed in Jacobi polynomials bases. Gauss quadratures mechanism for numerical integration is used to compute Jacobi transforms coefficients. To achieve desired compression, coefficients of small values are discarded in the reconstruction stage. As the derived polynomials use recurrence formula, rounding errors pile up during the computation and polynomials gradually denature with increase in order of the polynomial. ECG data compression based on B-spline basis functions is proposed by [24]. The position of the knots are computed using run-length coding. However, for false R-R complex new sequence of knots has to be sent, thereby increasing the overhead data resulting in increasing computational complexity. Nygaard and Haugland [25] proposed piecewise polynomial approximation for reconstructing the ECG signal by second order polynomials. Khetkeeree and Chansamorn [26] introduced signal reconstruction based on the second order tetration polynomial. Fundamental signals such as square, saw-tooth and sine wave with various sampling resolution were applied to test the interpolation performance. High values of peak signal-to-noise ratio (PSNR) were obtained for square wave and saw-tooth wave.

Now a days, long term ECG monitoring is applied for management of cardiovascular diseases where wireless technology is used to transmit ECG data through communication channels. Channel bandwidth can be optimized by performing ECG compression. ECG signals can be compressed using polynomial interpolation. Here high compression ratio can be achieved, since ECG signals can be reconstructed using few sampling points.

We propose here an algorithm to obtain an ECG approximating model based on lagrange form of hermite interpolating polynomial with chebyshev nodes. Hermite interpolating polynomials are more robust, since we have higher degree of freedom with derivative values as additional information which is equivalent to almost twice the order of the interpolating polynomial. This polynomial smoothly interpolates between the key-points and compresses the ECG data, thus facilitating less data for storage and transmission. In the process it also denoises the ECG signal in an efficient way while preserving the morphological features as required by the cardiologist. The organization of the paper is as follows: in section 2 we explain the research methodology of this work, in section 3 we provide experimental details and in section 4 we present the conclusions drawn out of our work.

2. RESEARCH METHOD

In real life applications experimental data are in the form of set of discrete data points and functional relation between input and output is nondeterministic. In such situations polynomial interpolation plays an important role in determining a polynomial matching the points. In our research work, we approximate an ECG signal f consisting of N ECG samples with lagrange form of hermite interpolating polynomial $Hp_n(x)$ using n chebyshev nodes. Our research methodology comprises mainly of five stages:

- Obtain raw discrete ECG data as .mat file from the MIT-BIH arrhythmia database now freely available on PhysioNet.
- At this stage preprocess and normalize the signals. The ECG data is converted into physical units (mV), then normalised by reducing the gain and re-scaled to limit the range within $[-1, 1]$.
- Map the 'n' chebyshev nodes, x_k, $k = 1, ..., n$ on the abscissa of time (seconds) with the equivalent ECG data to obtain them as function values fx_k, $k = 1, ..., n$.
- Obtain the derivatives $f'x_k$ at all $k = 1, ..., n$ points using numerical differentiation method.
- Construct the lagrange form of hermite polynomial with fx_k and $f'x_k$, $k = 1, ..., n$.

2.1. Function values at interpolating nodes

Since the ECG samples are obtained for an arbitrary length, we require to transform them to the designated interval and compute the function values (we consider the ECG signal as a function) at all the interpolating nodes. Let the ECG signal be sampled at a frequency F_s and the sampled values be defined as function values f, thus comprising of total N samples. With spacing $h = 1/F_s$, compute the end points of $[a, b]$ on the abscissa of time as,

$$a = 1/F_s, b = N/F_s$$

compute the n chebyshev nodes $x_k, k = 1, ..., n$ on $[a, b]$ as,

$$x_k = \left(\frac{a+b}{2}\right) - \left(\frac{b-a}{2}\right)\cos\left(\frac{2k-1}{2n}\pi\right), \quad k = 1, \cdots, n$$

find all the equivalent function values as,

$$fx_k = f(x_k[1:n])$$

any missing function value is evaluated with linear interpolation using the adjacent sampled values. Now, we have the data points in the form $(x_k, fx_k), k = 1, ..., n$.

2.2. Lagrange form of hermite interpolation

Hermite interpolating polynomials require the knowledge of the derivatives at the interpolating nodes. Since the function values are discrete, the derivatives are computed applying numerical differentiation methods. The numerical derivatives are computed using forward, central and backward differences. Use forward difference to compute $f'x_k$ at lower points of $[a, b]$,

$$f'x_k = \frac{1}{2h}[-3fx_k + 4fx_{k+1} - fx_{k+2}]$$

use backward difference to compute $f'x_k$ at upper points of $[a, b]$,

$$f'x_k = \frac{1}{2h}[-3fx_k - 4fx_{k-1} + fx_{k-2}]$$

use central difference to compute $f'x_k$ at intermediate points of $[a, b]$.

$$f'x_k = \frac{1}{2h}[fx_{k+1} - fx_{k-1}]$$

For the data of the form (x_k, fx_k) , $(x_k, f'x_k)$, $k = 1, ..., n$, the unique lagrange form of hermite polynomial $Hp_n(x)$ of degree $2n + 1$ that agrees with fx_k and $f^{'}x_k$ is given by:

$$Hp_n(x) = \sum_{k=1}^{n} fx_k A_{n,k}(x) + \sum_{k=1}^{n} f'x_k B_{n,k}(x)$$

where,

$$A_{n,k}(x) = [1 - 2(x - x_k)L^{'}_{n,k}(x_k)]L^2_{n,k}(x) \text{ and } B_{n,k}(x) = (x - x_k)L^2_{n,k}(x)$$

where, $L_{n,k}(x)$ denotes lagrange basis function of order n defined by,

$$L_{n,k}(x) = \prod_{i=1, i\neq k}^{n} \frac{(x - x_i)}{(x_k - x_i)}$$

the error using lagrange form of hermite interpolation with chebyshev nodes is given by,

$$E(x) = |f(x) - Hp_n(x)| \leq \frac{1}{2^n(n+1)!}\left|\frac{(b-a)}{2}\right|^{(n+1)} \max_{a\leq\xi\leq b} |f^{(n+1)}(\xi)|$$

if $E \geq \varepsilon$, where the tolerance $\varepsilon = 10^{-2}$, then n is increased by 10 and the entire procedure is repeated.

3. RESULTS AND ANALYSIS

The proposed algorithms are implemented in MATLAB (R2013b) version. Each part of the proposed ECG approximation algorithm is written in the .m file as a subroutine module. All the computations are carried out on ECG signals taken from MIT-BIH arrhythmia database available on PhysioNet [27]. We consider here various signals of channel 1, sampled at 360 Hz with a resolution of 11 bits per sample with duration of 5 seconds resulting in 1,800 samples. These sample points are the ECG signal magnitudes obtained at equal intervals of '$1/360$' second. We perform the fidelity assessment of the proposed approximation method using the performance or error measures as - root mean square error (RMS), percentage root mean difference (PRD), signal to noise ratio (SNR), and compression ratio (CR). Here, we consider CR as the ratio of the number of bytes in the uncompressed representation to the number of bytes in the compressed representation.

To test the efficacy of our proposed method we apply the developed algorithms on 12 records shown in Figures 1 and 2 with duration of 5 seconds and approximate them in the form of respective polynomials with 300 chebyshev nodes. All the 12 obtained results are illustrated in Figures 1 and 2, Figure 1(a) #100, Figure 1(b) #104, Figure 1(c) #108, Figure 1(d) #112, Figure 1(e) #115, Figure 1(f) #117, and Figure 2(a) #122, Figure 2(b) #201, Figure 2(c) #205, Figure 2(d) #207, Figure 2(e) #214, Figure 2(f) #220 depicting the original signals and the reconstructed polynomials in red and blue colours respectively.

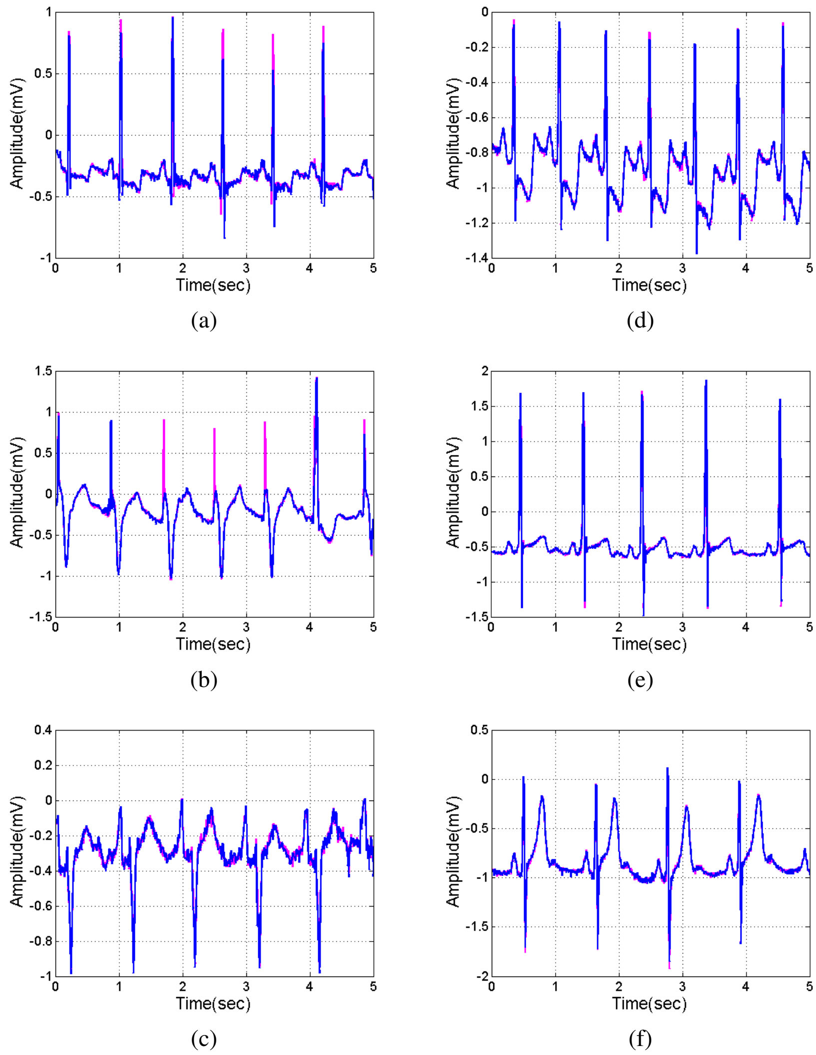

Figure 1. Original noisy ECG signals (pink) and reconstructed samples by proposed method (blue): (a) ECG record #100, (b) ECG record #104, (c) ECG record #108, (d) ECG record #112, (e) ECG record #115, and (f) ECG record #117

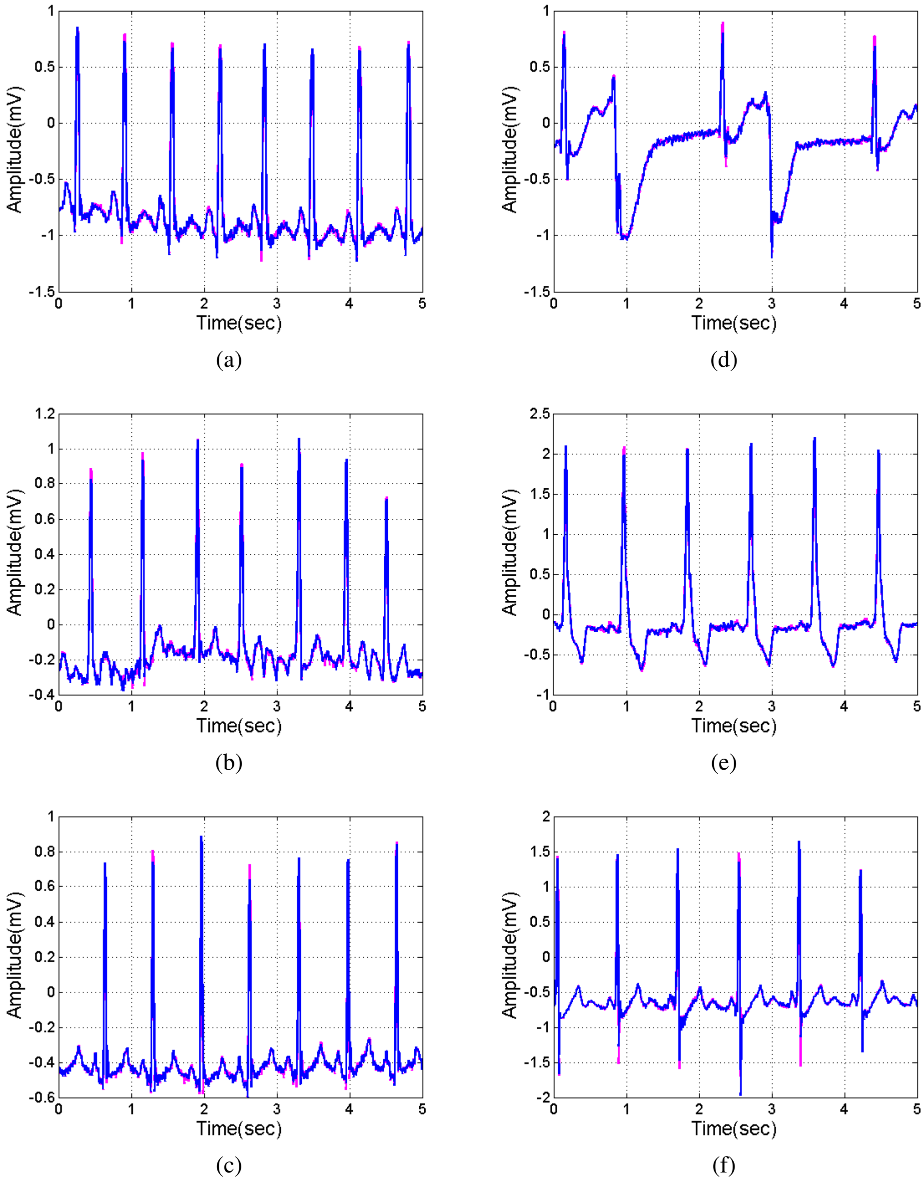

Figure 2. Original noisy ECG signals (pink) and reconstructed samples by proposed method (blue): (a) ECG record #122, (b) ECG record #201, (c) ECG record #205, (d) ECG record #207, (e) ECG record #214, and (f) ECG record #220

Since the proposed method is an extension of the method proposed by Yadav and Ray [21], we deem it fit to compare the performance statistics of the proposed method with the latter. Yadav and Ray [21], have approximated all these records of same duration with assorted noise levels using lagrange interpolating polynomial with 400 chebyshev nodes respectively. The performance statistics of the method by Yadav and Ray, and the proposed method are reported in Table 1. It is worth mentioning that in the process of approximating, both the methods eventually denoise the ECG signals.

Comparing the respective entries of Table 1 for each ECG record, we observe that lower order hermite form of interpolating polynomial outperforms the lagrange form in all performance metrics. Lower values of RMS are indicative of least distortion and better approximation. The values of CR in both the methods remain constant for all the signals, because the number of samples and the respective number of interpolating nodes are persistent in all the signals.

The two important features of a compression algorithm are the compression measure and the reconstruction error. Not many approximating methods are available in the existing literature for ECG signals. To have a comprehensive review of the proposed method, we abstractly compare the performance of the proposed method with two existing recent works on ECG compression. The identified methods are: Yang *et al.* [14] using empirical mode decomposition (EMD) and Hamza *et al.* [28] based on discrete wavelet transform (DWT) and dual encoding technique.

Table 1. Comparison of the proposed method with Yadav and Ray [21] for signal length of 5 sec

Record	Yadav and Ray [21] with $n = 400$				Proposed method with $n = 300$			
	RMS	PRD	SNR	CR	RMS	PRD	SNR	CR
100	0.11	15.75	8.45	4.49	0.04	12.27	11.44	6.00
104	0.06	18.92	12.34	4.49	0.07	19.85	11.86	6.00
108	0.02	6.39	16.76	4.49	0.03	7.81	15.33	6.00
112	0.02	2.55	17.09	4.49	0.02	1.70	21.35	6.00
115	0.09	14.72	10.57	4.49	0.04	6.21	18.07	6.00
117	0.03	3.71	16.81	4.49	0.02	2.73	19.71	6.00
122	0.04	4.99	17.85	4.49	0.03	3.53	21.21	6.00
201	0.02	9.22	17.29	4.49	0.02	8.14	19.68	6.00
205	0.05	11.43	10.51	4.49	0.02	4.88	18.33	6.00
207	0.02	5.10	23.56	4.49	0.02	6.97	21.93	6.00
214	0.04	8.79	19.57	4.49	0.03	7.67	21.96	6.00
220	0.11	15.75	8.70	4.49	0.06	8.60	14.07	6.00

For comparison with Yang *et al.* [14] method, we choose 8 MIT-BIH arrhythmia data sets [27] as test signals with time period as 4.2 seconds and sampling rate as 360 Hz for all the signals. The 8 records are referred as #100, #103, #107, #109, #116, #117, #119, and #200. To evaluate the quality of the proposed algorithm we use RMS and CR as the performance measures and illustrate the results as bar graphs in Figure 3 and Figure 4. From the comparisons we can easily infer that the proposed method fairs very well in RMS metric and compares well in CR metric.

For comparison with Hamza *et al.* [28] method, we choose 5 MIT-BIH arrhythmia data sets as test signals with time period as 10 seconds and sampling rate as 360 Hz for all the signals resulting in 3,600 samples. The 5 records are referred as #100, #109, #115, #119, and #200. To evaluate the quality of the proposed algorithm we use RMS as the performance measure and depict the results in Figure 5 from where we observe that the proposed method performs very well. Here, we haven't considered the comparison of CR since we differ in our definitions.

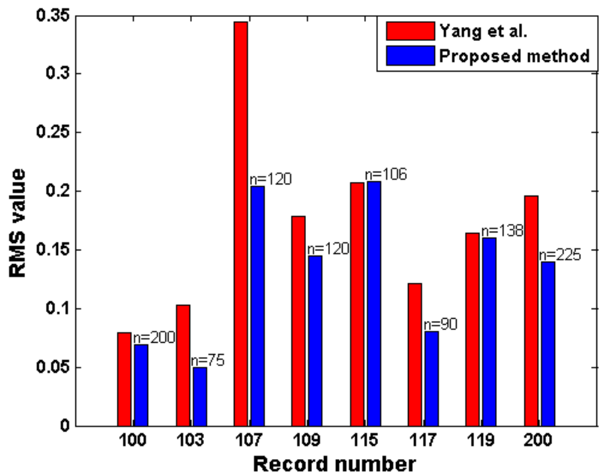

Figure 3. Bar graph of RMS values of various records with signal length of 4.2 sec obtained by Yang *et al.* [14] and the proposed method

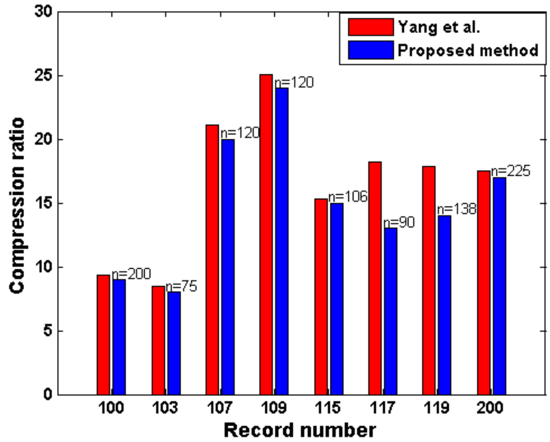

Figure 4. Bar graph of CR values of various records with signal length of 4.2 sec obtained by Yang *et al.* [14] and the proposed method

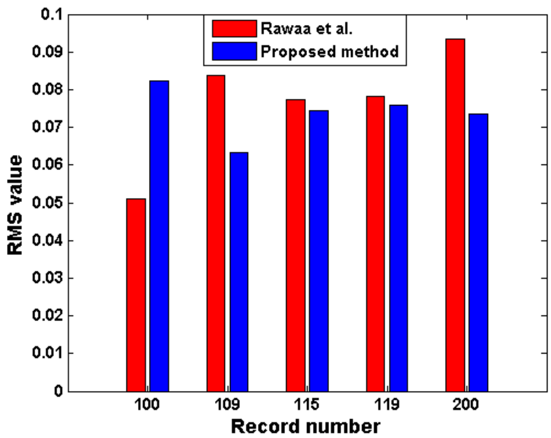

Figure 5. Bar graph of RMS values of various records with signal length of 10 sec obtained by Hamza *et al.* [28] and the proposed method

4. CONCLUSION

In this work, the superiority of the proposed approximation model of lagrange form of hermite polynomial interpolation with chebyshev nodes is established by applying on various ECG signals taken from MIT/BIH arrhythmia database and comparing with few existing methods taken from recent literature. From all the analysis we infer that the proposed method of approximation outperforms all the methods in most of the metrics. The proposed method compresses ECG signal thus reducing the memory requirement. Apart from this, the proposed scheme not only eliminates noise, but also preserves important morphological features required for analysis of various conditions like arrhythmias, inadequate coronary artery blood flow, electrolyte disturbances, and cardiomyopathy. Most significant is that the proposed method is able to convert the ECG signal into a polynomial; and all polynomial operations emphasize can be applied to extract various morphological features for the diagnosis of various diseases that are reflected in the ECG. The proposed model can also be extended in approximating other time series data such as economic and sales forecasting, budgetary and stock market analysis, yield projections, process and quality control, to predict the future price of the stock market, and exchange rate forecast.

Furthermore, the proposed method is riddled with certain challenges. In case of critical base line wander additional preprocessing step has to be applied. Moreover, detrending of time series data is necessary whenever there is a base line drift in the signal.

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