ON A COMPRESSION ALGORTHM FOR ECG SIGNALS

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ABSTRACT

The paper presents a new algorithm for ECG signal compression based on local extreme extraction, adaptive hysteretic filtering and LZW coding. Basically the method consists in smoothing the ECG signal with a Savitzky-Golay filter, extraction of the local minima and maxima, a hysteretic filtering and LZW coding. The reconstruction of the ECG signal is done by cubic interpolation.
The algorithm is robust with respect to noise, has a rather small computational complexity and provides good compression ratios with excellent reconstruction quality.
The results of the algorithm compare favourably to other algorithms like AZTEC, SAPA, TP, CORTES, SPHIT, JPEG2000 and wavelet-based ECG compressions.

1. INTRODUCTION

It is well known that modern clinical systems require the storage, processing and transmission of large quantities of ECG signals. The feature of ECG compression algorithms is to achieve a reduced information rate, while retaining the relevant diagnostic information in the reconstructed signal. Efficient and low computationally complexity compression schemes for medical signals are useful in applications related to mobile healthcare and real-time patient monitoring but also in optimized databases. A data compression algorithm should allow reproducing of the data with acceptable fidelity.
Many algorithms for ECG compression have been proposed in the last thirty years; they have been mainly classified into three major categories: direct data compression, transformation methods, and parametric techniques [1].
The criteria for testing the performance of the compression algorithms consist of three components: compression measure, reconstruction error and computational complexity. The compression measure and the reconstruction error depend usually on each other and determine the rate-distortion function of the algorithm. The computational complexity component is related to practical implementation consideration and is desired to be as low as possible, especially for portable equipments. [2]
The compression ratio (CR) is defined as the ratio of the number of bits of the original signal to the number stored in the compressed signal.
One of the most difficult problems in ECG compression applications and reconstruction is defining the error criterion. In most ECG compression algorithms, the percentage root-mean- square difference (PRD) measure is employed. Other error measures such as the PRD with various normalizations, root mean square error (RMS) and signal to noise ratio (SNR) are used as well [2]. However, the clinical acceptability of the reconstructed signal should always determine through visual inspection as well.

2. METHOD

The proposed method is a hybrid one i.e., a combination between signal processing (resembling the peak-picking compression techniques [3], [4]) and information transmission theory based techniques. It can be viewed as two cascaded blocks. The first block extracts the essential information from the ECG signal. The signal reconstruction is based on the localization of the most significant part of the local minima and maxima (amplitude and location) together with some other points in order to decrease the error. The second block encodes the information from the first block, through delta coding followed by the LZW coding.

2.1 The pre-processing

The pre-processing stage consists of a filtering with a 6-degree Savitzky-Golay filter (SGF) using a 17 points constant window. SGF’s also called digital smoothing polynomial filters or least-squares smoothing filters are typically used to "smooth out" a noisy signal whose frequency span (without noise) is large. They perform much better than standard averaging FIR filters, which tend to filter out a significant portion of the signal's high frequency content along with the noise. Although SGF’s are more effective in preserving the high frequency components of the signal, they are less successful than standard averaging FIR filters in rejecting the noise. SGF’s are optimal in the sense that they minimize the least-squares error in fitting a polynomial to frames of noisy data.[5]

2.2 The ECG skeleton

The main idea of this step is to extract the local minima and maxima from the filtered ECG signal and rounding the extracted values to the nearest integer. This is equivalent to a non-uniform sampling followed by a quantization. We will call the resulting discrete signal with non-uniformly spaced samples the signal skeleton. Knowing the location and the amplitude of the local extremes it is possible to reconstruct the ECG signal without loss of relevant information. This fact was confirmed by the error and the distortion values between the original ECG signal and the reconstructed ECG signal as well as by specialist physicians through visual inspection.

2.3 The hysteretic filtering

In order to improve the compression rate without significantly increasing the distortion between the original ECG

signal and the reconstructed one from the skeleton samples having variation of the extreme values under a prescribed threshold have been discarded. This has been done with a hysteretic filtering in two steps.
In the first step the aim was improving the compression quality. The hysteretic filtering is characterized by a threshold denoted TH2. Samples for which the difference from previous ones is less than TH2 are discarded. The calculation of TH2 consists in the computation of a first threshold,

$$TH1 = \sqrt{ST(A[n])}$$

where ST is the standard deviation of A[n]=|amp[n]-amp[n-1]| and amp[n] represent the amplitude of the n-th sample of the skeleton. The standard deviation of skeleton samples having amplitude variations A1[n]=|amp[n]-amp[n-1]| less than TH1 is then calculated. The TH2 threshold is determined using the formula

$$TH2 = k \cdot ST(A_1[n])$$

where k was initially chosen equal to 2.
The reconstruction errors based on the skeleton obtained in the above manner are rather high mainly for the QRS complex when adjacent skeleton samples are rather far one to the other.
The reconstruction error can be decreased by adding intermediate points to the skeleton resulted after the application of the TH2 threshold. The location of the intermediary points which will be added to the skeleton is determined through a third threshold, TH3 as follows: where the absolute value of the difference between two the successive amplitudes is higher than TH3, a sample of the original signal taken in the middle of the distance between the skeleton samples is added to the skeleton.
This TH3 threshold has been adopted according to the following formula:

$$TH3 = \frac{1}{4N}\sum_{n=1}^{N} A_1[n]$$

2.4 The LZW coding

The LZW coding [6], [7] is a lossless “dictionary based” compression algorithm which looks for repetitive sequences of data and builds a dictionary based on them.
As a preliminary step, the obtained skeleton is delta coded both for amplitudes and distances. The LZW algorithm is then used to compress the results.

3. EXPERIMENTAL RESULTS AND DISCUSSION

The MIT-BIH Arrhythmia database [8] was used to evaluate the proposed compression algorithm and compare it with other known compression methods.
The ECG signals were digitized through sampling at 360 samples per second, quantized and encoded with 11 bits. For the tests the first 10000 samples out of 24 MIT-BIH records [8] have been used.
Even though linear interpolation has been used as well, the results reported in this communications are based only on cubic interpolation which gave better results.
The results were obtained by encoding and decoding the original signal files.
The resulted PRD shows very low values. Since the variability of the signal around its baseline is what should be preserved and not the baseline itself, the performance measure used to reveal the accuracy of the algorithm was the variance of the error with respect to the variance of the signal. Another possibility is to use the normalized PRD (PRDN).
The average partial compression ratios (without LZW coding) and average PRD (PRDN, RMS and SNR) for the 24 data records are shown in *Table 1*.

Average delta CR	Average PRDN	Average PRD	Average RMS	Average SNR
7.4181	17.3742	1.1703	11.3507	16.2824

Table 1 - *Average partial results of the compression algorithm for 24 of records*

After the pre-processing stage without LZW compression, the highest compression ratio (CR=13.79:1 and PRD=4.13%) was achieved for the record 217. The lowest compression ratio was achieved for the record 232 (CR=2.58:1 and PRD=0.29%).
The compression efficiency of an algorithm can be evaluated using BPS [bit/sec] (amount of compressed data / original signal duration) and/or B/sample [bit/sample] (amount of compressed data / amount of original data).
The two vectors (amplitude and location) representing the skeleton from the pre-processing stage and stored in delta coded form are compressed with LZW. For the location and amplitude vectors the average compression rate tends to 2:1 and to 3:1 respectively.
The mean value of the PRD is 1.17%, with extremes values of 0.29% and 4.13%. Only for five records higher values have been obtained. In these cases, the performances are weaker due to the presence of noise.
After the pre-processing stage (including the Savitzky-Golay filtering, extracting of all local maxima and minima, hysteretic filtering, followed by the delta coding) an average compression ratio of 7.41:1 and an average PRD of 1.17% were obtained. After the LZW compression applied to the two previously obtained vectors, a final average compression rate of 18.27:1 is obtained (see *Table 2*). Since the LZW compression is a lossless compression, the PRD is conserved.

Average CR	Average PRDN	Average PRD	Average RMS	Average BPS
18.27:1	17.3742	1.1703	11.3507	260

Table 2 - *Average final results of the compression algorithm for 24 of records*

A high quality of the reconstructed signal was obtained as shown in *Figure 1*and *Figure 2* where the extreme cases are presented.
Good reconstruction has been obtained in all cases including that with the highest compression ratio, respectively PRD, (record 232).
After using the LZW algorithm, the highest and lowest compression ratios were achieved for records 217 and 232, (CR of 34:1 and 6.37:1 respectively).

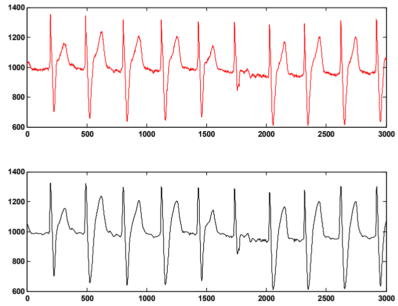

Figure 1 *– Original and reconstructed ECG signals for record 217 (CR=34:1, BPS=127 and PRD=4.13%)*

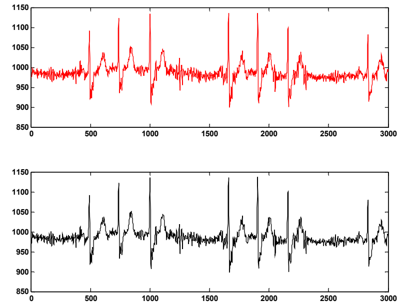

Figure 2 *– Original and reconstructed ECG signals for record 232 (CR=6.37, BPS=678 and PRD= 0.29%)*

The intermediate and final results i.e., before and after the LZW compression of all 24 records are shown in *Table 3*.

Record	Delta preprocessing CR	PRDN	PRD	RMS	SNR	CR with LZW	BPS	B/sample
232	2,59	12,31	0,30	2,91	18,19	6,37	678	1,8824
219	8,54	9,36	0,92	8,38	20,58	21,05	205	0,57005
217	13,80	34,20	4,13	41,94	9,32	34,00	127	0,35295
215	5,52	20,61	1,08	10,81	13,72	13,59	318	0,8827
214	9,19	31,25	2,94	29,11	10,10	22,62	191	0,5304
213	7,79	7,48	0,90	8,47	22,53	19,19	225	0,6253
212	7,82	17,16	1,13	11,21	15,31	19,25	224	0,62335
209	7,36	19,78	0,95	9,46	14,08	18,12	238	0,66235
208	8,36	17,50	1,97	19,76	15,14	20,58	210	0,58305
207	7,05	7,42	0,43	4,35	22,59	17,37	249	0,69095
205	5,78	10,28	0,40	3,80	19,76	14,25	303	0,8424
202	6,31	18,23	0,87	8,69	14,79	15,54	278	0,7722
201	8,06	24,63	0,98	9,71	12,17	19,85	218	0,6045
119	7,60	8,34	1,03	8,89	21,57	18,72	231	0,6409
118	4,76	13,19	1,19	9,83	17,59	11,73	368	1,0231
117	5,17	11,54	0,61	5,30	18,76	12,74	339	0,94185
115	7,61	26,72	1,86	17,26	11,46	18,76	230	0,6396
106	6,68	11,61	0,91	9,01	18,71	16,47	262	0,72865
105	10,03	16,86	1,06	10,31	15,46	24,71	175	0,48555
104	5,80	13,66	0,82	8,05	17,29	14,28	303	0,84045
103	9,99	9,46	0,62	6,04	20,48	24,62	175	0,4875
102	6,76	14,92	0,55	5,33	16,53	16,65	260	0,72085
101	7,32	48,38	2,02	19,56	6,31	18,03	240	0,6656
100	8,14	12,10	0,44	4,22	18,35	20,05	216	0,59865

Table 3 *- Results of the compression algorithm for 24 records*

As already mentioned, the performance evaluation of different coders should be doubled by visual inspection of the reconstructed signals by a cardiologist. Each compressed signal was scored by comparing its diagnosis with that based on the original signal. If the diagnoses were the same, the compressed signal was considered to be "correctly diagnosed". If the diagnoses were different, or if the quality of the compressed ECG was too poor to make a diagnosis, the compressed signal was considered to be "incorrectly diagnosed". In our cases the verdict of the cardiologist physician was "correctly diagnosed" for all records.

Once an ECG decoded signal has been validated by the physician, various compressions leading to close values of the CR and PRD can be compared using a "quality score" (QS) defined as the ration between CR and PRD. A high score represents a good compression as far as it has been validated by visual inspection as well.

As an example, in order to compare three compressed records with close values of CR and PRD records 117 (CR=12.74 and PRD=0.61), 119 (CR=18.72 and PRD=1), and 104 (CR=14.27 and PRD=0.8) the above scores were: QS=20.81 for the record 117, QS=18.24 for the record 119 and QS=17.44 for the record 104.

The compression quality is proportional to the score value. For the 24 records analyzed, an average qualitative score of 20.73 was obtained, with the maximum value of 45.52 for the record 100 and minimum value of 7.69 for the record 214.

For all cases presented so far, the value of the parameter k used for the calculations of the TH2 was equal to 2. The compression results for the case when k took values between

1.5 and 2.5 are shown in the *Table 4.* However, a conclusion about compression quality only using the values from the *Table 4* cannot be drawn.

Visual inspection, the ultimate validation of the results, showed that the acceptable values for k should not surpass 2.3 was confirmed by the error analysis using PRD.

parameter	Average of CR	Average of PRD
1.5	15,484791	1,094590
1.6	15,952378	1,115325
1.7	16,595180	1,136447
1.8	17,299697	1,143238
1.9	17,761039	1,147850
2	**18,2725**	**1,1703**
2.1	19,117721	1,178093
2.2	20,108151	1,223468
2.3	20,501148	1,227835
2.4	21,294114	1,242212
2.5	22,014218	1,283955

Table 4 *- Results of the compression algorithm for values of the k parameter in the formula of TH2 between 1.5 and 2.5*

The proposed method has been compared with some other compression techniques [1], [9], [10], [11], [12] for the record 117 and the results are presented in *Table 5*.

Algorithm	PRD	CR
Wavelet and Huffman [9]	3.2	9.4:1
JPEG2000 [12]	0.86	8:1
	1.03	10:1
SPHIT [11]	1.18	8:1
Hilton [10]	2.6	8:1
Djohn [10]	3.9	8:1
AZTEC [1]	28	10:1
TP [1]	5.3	2:1
CORTES [1]	7	4.8:1
Fan/SAPA [1]	4	3:1
Proposed	**0.61**	**12.74:1**

Table 5 *– Comparison between the proposed method and other compression algorithms (the record 117)*

The average PRD or RMS and average CR values obtained using the proposed method is compared to other methods in literature [11], [12], [13] in *Table 6*.

Algorithm	Average of errors (PRD or RMS)	Average of CR
Wavelet [13]	18.2 RMS	21.4:1
SPHIT [11]	3.57 PRD	12:1
	4.85 PRD	16:1
	6.49 PRD	20:1
JPEG2000 [12]	2.19 PRD	12:1
	2.74 PRD	16:1
	3.26 PRD	20:1
Proposed	**1.17 PRD** **11.35 RMS**	**18:27:1**

Table 6 *- PRD comparison of different algorithms*

4. CONCLUSIONS

A skeleton-based adaptive hysteretic filtered ECG data compression technique has been proposed. It was tested and compared with different ECG compression algorithms.

The proposed method is rather fast and easy to implement and leads to high CR with a good reconstructive quality.

The mean value of the CR for the 24 records analyzed is 18.2725 and the PRD=1.17%. The best results were for the record 217 (CR=34:1 and PRD=4.13%) and the weakest for the record 232 (CR=6.37:1 and PRD=0.29%).

All clinical information is preserved after compression with the proposed algorithm. The algorithm was tested for the compression of normal, abnormal and affected by noise ECG signals extracted from the MIT-BIH database.

Visual inspection by the cardiologist physician of the original and reconstructed ECG signals, led to "correct diagnose" for all records.

By means of hysteretic filtering adapted to the nature of the signal the compression ratio and distortions of the proposed compression algorithm can be controlled.

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REFERENCES

[1] S.M.S. Jalaleddine., "ECG Data Compression Techniques - A Unified Approach", IEEE Trans. on Biomed. Eng., Vol. 37, No. 4., 1990, pp. 329-343;

[2] Y. Zigel, A. Cohen, and A. Katz, "ECG Signal Compression Using Analysis by Synthesis Coding", IEEE Trans. on Biomed. Eng, Vol. 47, No. 10, October, 2000, pp. 1308-1316;

[3] R.W. McCaughern, A.M. Rosie, F. C. Monds, "Asynchronous data compression techniques", in Proc. Purdue Centennial Year Symp. Information Process., vol. 2, Apr. , 1969, pp. 525-531;

[4] E.A. Giakoumakis, G. Papakonstantinou, "An ECG data reduction algorithm", Comput. Cardiol., Boston, Ma, Oct, 1986, pp. 675-677;

[5] „Numerical Recipes in C: The Art of Scientific Computing", Cambridge University Press, 1992;

[6] K.R. Rao and P.C. Yip., "The Transform and Data Compression Handbook", CRC Press LLC, 2001;

[7] M. Crochemore and T. Lecroq, Text data compression algorithms, "Algorithms and Theory of Computation Handbook", M. J. Atallah, ed., CRC Press, Boca Raton, 1998.

[8] http://www.physionet.org/physiobank/database/mitdb/

[9] A.Al-Shrouf, M. Abo-Zahhad, S. M. Ahmed, "A novel compression algorithm for electrocardiogram signal based on the linear prediction of the wavelet coefficients", Digital Signal Processing, vol. 13, 2003, pp. 604-622;

[10] M.L. Hilton, "Wavelet and Wavelet Packet Compression of Electrocardiograms", IEEE Trans. on Biomed. Eng., Vol. 44, No. 5, May, 1997, pp.394-402;

[11] Z. Lu, D. Y. Kim, and W. A. Pearlman, "Wavelet Compression of ECG Signals by the Set Partitioning in Hierarchical Trees (SPIHT) Algorithm," IEEE Transactions on Biomedical Engineering, Vol. 47, July, 2000, pp. 849-856;

[12] Ali Bilgin,, Michael W. Marcellin, Maria I. Altbach, "Compression of Electrocardiogram Signals using JPEG2000", IEEE Transactions on Consumer Electronics, Vol. 49, No. 4, November, 2003, pp. 833-840;

[13] B. Bradie, "Wavelet Packet-Based Compression of Single Lead ECG", IEEE Transactions on Consumer Electronics, Vol. 43, No. 5, May, 1996, pp. 493-501;