ECG Estimation Using a Saw-Tooth Pattern in Remote Environments

MM Elena, A Martín, JM Quero

University of Seville, Seville, Spain

Abstract

In this paper a simple and viable on-line method to transmit ECG under hardware restricted environments is derived and its performance illustrated in simulation studies. The proposed scheme makes use of an ECG signal lossless compression technique for the communications channel optimization. Obtaining a better compression rate guarantees both the sending costs and the memory resources reduction. Simulation results show lossless compression ratios superior to 50% without restrictive requests to the application system. The main success of this research is that it gives adequate assurance for the implementation of a feasible and reliable prototype in mobile environments for remote monitoring.

1. Introduction

Lossless compression is required in some medical applications, but most of the ECG encoding schemes is based on the original signal approximations that can lose some useful features for further analysis of ECG signals [1,2]. It can be also mandatory for data where losses are not acceptable or because of legal questions [3]. In contrast to the lossy compression algorithms which achieve a higher compression, medical distrust in discarding relevant information for visual diagnostic leads to the choice of a lossless one.

The initial system is the remote monitoring device Cardiosmart [4]. The portable systems is acquiring, encoding, transferring and monitoring ECG to be used by patients at the same time they need a clinical test because of a heart disease. Main difficulties associated to on-line methods come from limitations in the available resources and the required compromise between data stream acquisition and transmission rates. This application has 1.5 seconds available to manage the biological signals because the data streams are sent at intervals separated by this time. This management includes signal processing and communication setting up with the hospital. The technology implemented to support the communication is provided by a mobile telecardiology device.

The compression need comes up in the search of costs and memory minimization. Cardiosmart makes use of a real-time lossy compression technique but the medical distrust gives rise to the interest of studying lossless compression methods. The contribution to Cardiosmart system is estimating ECG to achieve lossless compression in a remote device.

The novelty in this study is to characterize a generic and static probability distribution estimator built from saw-tooth behaviour. In particular, the digitizing of electronic parameters: sampling frequency and resolution are considered to build the model in order to increase the signals redundancy.

First of all, we shown in table 1 a comparative between different methods found in previous works. The merit figure used is the compression ratio (CR) defined as [5]:

$$CR = \frac{\text{Number of bits in}}{\text{Number of bits out}}$$

Irreversible techniques have losses coming from the signal approximations [6,7] or transformations [8,9] but they are omitted in Table 1 because the authors make an unclear quantification of the error measurements or use different parameters making impossible an unified comparison criterion. The sampling rate and the resolution of ECG signals in each algorithm are reported because they are determinant for the value of the compression rate. Flexibility of sampling frequency and resolution leads to difficulties for comparison of the different compression methods [5] as we will explain later.

The best outcome is achieved with ALZ77 [10] but this method is unfeasible to be supported by our application which is performed in real-time: a big processing time, due to the most time-consuming phase which is searching for a best match in the window area [5], and a large memory resources are needed.

Thus, we concluded that the most suitable method for this application is the entropy coding of 1st difference (Huffman 1st difference). This paper shows the simulations and conclusions achieved.

Method	CR	Sampl. Rate (Hz) (Resolution(bits))
2º differences entropic codification [11]	2.8	250(12)
DPCM-Delta codification with threshold [6]	4.0	300(8)
DPCM-Linear prediction[7]	2.5	250(12)
Ortogonal Transf. CT,KLT,HT [8]	3.0	250
Dual application KLT [9]	12.0	250(12)
ALZ77,Tolerance 0 [10]	3.2	250(8)

Table 1. Previous algorithms results

2. Model probabilities zones

The Huffman variable length coding scheme provides a method for the assignment of code words for M symbols with lengths ranging from 1 to $\lceil \log 2M \rceil$, based on the probability distribution. Values with higher probability are assigned shorter code lengths and values with lower probability are given longer code lengths [7]. The 1st difference Huffman technique uses the zero order predictors (ZOP) of the ECG signals:

$$d1_n = y_n - \hat{y}_n = y_n - y_{n-1}$$

The use of the differences takes advantage of the correlation between adjacent signal samples. A new signal with two advantages is obtained from the original one: the samples probabilities have no relation with the baseline ECG value and have more redundancy.

Although code length determination is almost unique in every technique, the different encoding procedure may consume different memory spaces, as well as different processing time. There are different variants of Huffman encoding: static, semi-adaptative and adaptative codification. The static one always uses the same Huffman table, whoever the patient is. Semi-adaptative and adaptative kinds are not suitable because they need a lot of time to build the Huffman tables in a real-time application (consider for instance, a resolution of 10 bits the difference alphabet will have 2047 symbols). Once we choose static Huffman encoding of 1st difference we need a probabilistic model to achieve a good ECG general compression.

The model choice should be derived by the use of available previous data knowledge to be modeled. Figure 1 shows the probability distribution (PD) of 1st differences of an ECG captured by our system with 300Hz of sampling frequency and a resolution of 10 bits and with 8 bits (figure 1).

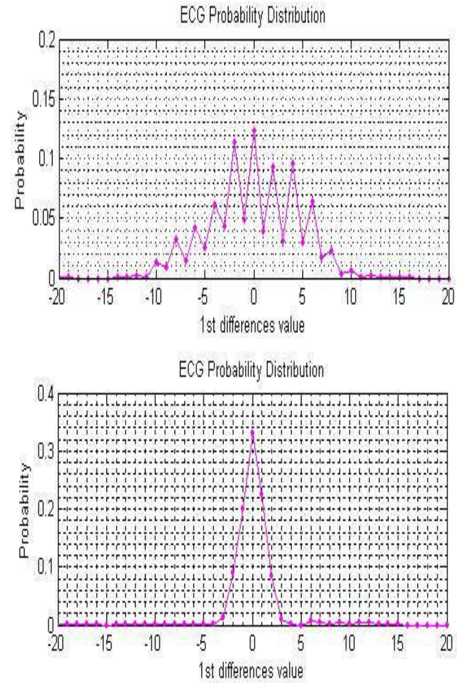

Fig 1.- 1st differences PD (300Hz, 10 bits) (up)
1st differences PD (300Hz, 8 bits) (down)

The fact of using less resolution has an immediate consequence: a lower signal accurate. But also the range of possible digital values is reduced so the signal redundancy increases. The ADC quantization steps cause the different shapes for the probability distribution, depending on the resolution. Considering that most of the ECG samples of the distribution are concentrated around the null difference and a great deal of the 1st difference symbols has null probability, 3 zones are distinguished:

1. Zone A: [ZAI]∪[ZAD]: Differences with null value either left or right extreme. where 'za' is the last null value. The differences probabilities within zone A add up to 0%.
2. Zone B: [ZBI]∪[ZBD]: Symbols take the same probability value at left or right extreme. They add 10% or less from the whole probability.
   The probability pzB/C adds of zone B/C value is calculated:
   $$pZB = \frac{1 - pZC}{2 \cdot (za - zb)}$$
3. Zone C: (ZC) Most significant symbols round '0' difference value. It includes all the symbols in the interval
   $$[\text{'}-zb+1\text{'}, \text{'}zb-1\text{'}]$$
   The differences add up to 90% or more, built from medium value between samples of the same magnitude and opposite sign.

The following figure shows the model zones. The horizontal axis represents the differences values and the vertical axis represents the probabilities for an electrocardiogram adquiring with a frequency rate of 300Hz and 10 bits o resolution.

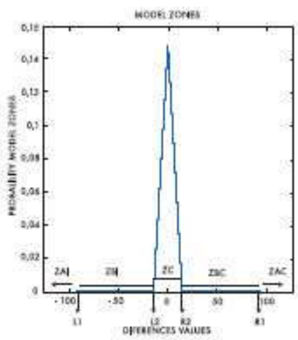

Fig 2.- 1st differences probability distribution

After establishing the model, the next issue is the creation of the variable-length code table used by the 1st differences Huffman algorithm.

3. Results and discussion

In this study, the influence of sampling frequency and resolution in the lossless compression ratio is shown. The developed models have been performed by using captured ECG with different bit resolution and sampling rate as follows:

1. Starting from the captured ECG we build from each one its symmetric model.
2. Calculating the arithmetic mean value[1] for each symbol making use of the symmetric models built under identical sampling features in step 1.

Designing models are presented in the table 2.

Model	Sampling Frequency (Hz)	Resolution (bits)
1	300	10
2	300	8
3	360	10
4[2]	360	10
5	500	10
6	750	10
7	1000	10

Table 2. Summary of models and parameters

Model 1 is presented as example in figure 3. It can be appreciated the symmetry of the probability distribution model.

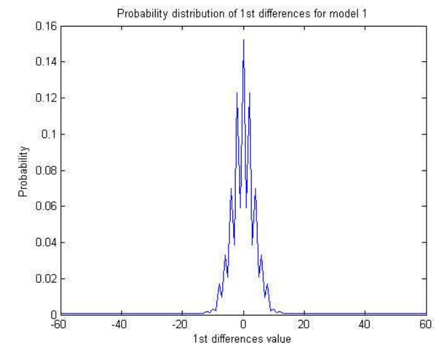

Fig 3. 1st difference probability distribution (model 1)

The tests have done with both ECG signals, captured by an in-home portable device and MIT-BIH DB records. The sampling frequency and resolution values of these test samples vary from between 250 to 360Hz and from between 10 to 12 bits respectively.

Resolution: Increasing the ADC bits number presents more accurate signals measurements but the compression ratio is insignificantly increased by small variations. The number of bits of the ECG used to build the model has to be bigger than the precision of the ECG to compress. This fact is independently of the model we use. This fact is independently of the model we use.

This behaviour is summarized in figure 4 where the performance measurements of CR mean values for model 3 is represents depending on resolution (horizontal axis), using an ECG captured with different frequencies.

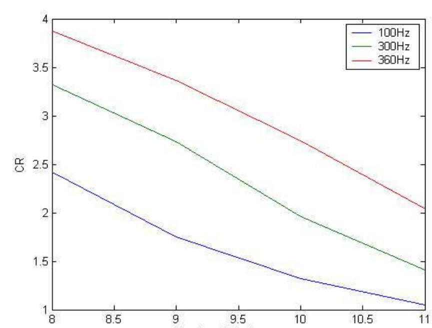

Fig 4. CR mean values vs. Resolution (Model 3)

Frequency sampling: Increasing the frequency sampling will also lead to more accurate measurements of the signals as well as to strength the dependency of consecutive samples; redundancy between samples will increase improving the CR as shown in figure 5. But increasing the frequency sampling slows down the system processing speed. So the model sampling rate has to be smaller than the ECG sampling rate to compress. Figure 5 shows this frequency dependence

[1] The Huffman coding assuming that the probability symbol is higher or lower but not the same value.
[2] Model number 4 has the same rates than model number 3 but models 4,5,6 and 7 were built with ideal ECGs [12].

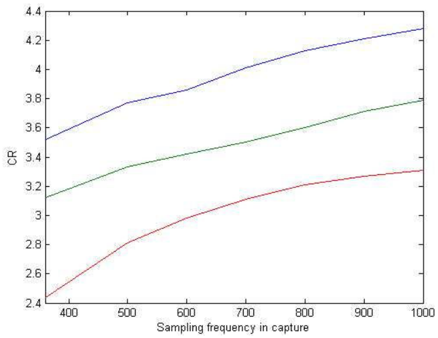

Fig 5. CR mean values vs. Frequency (Model 3)

In figures 6 and 7, the CR mean values for different models are represented modifying the resolution sampling. Figure 7 shows the outcomes for ECG captured with 360Hz which is the typical frequency used in the MIT-BIH database.

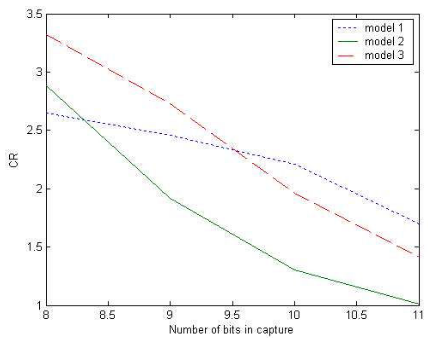

Fig 6. CR mean values vs. Resolution (300 Hz)

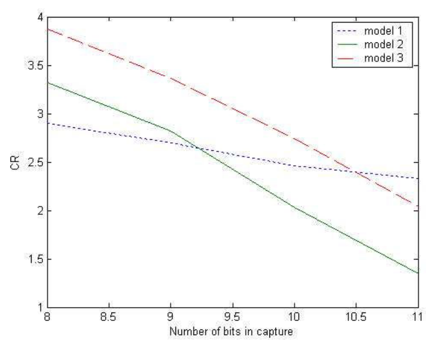

Fig 7. CR mean values vs. Resolution (MIT-BIH)

The best model must be choosing depending on the sampling rates used to capture the ECG signal. In our system, a fixed resolution of 10 bits is given by the ADC. The sampling frequency can be chosen between 100 and 300Hz. For preserving ECG spectral information, 300 Hz is used. In every experimental results, the model which achieves the best CR mean values is model number 1 built with ECG captured with 300Hz and 10 bits.

4. Conclusions

Two results are derived from this study, first, the dependence of the compression ratio on the signal resolution and its sampling frequency; second, the optimum model only exists defining an ECG with a specific sampling rate. As a conclusion the achieved estimator improves the ECG compression when the pattern redundancy is lower than the signal one.

A lossless coder based on a saw-tooth probability model has been successfully presented. It makes use of the Huffman method and supplies good performance to compress ECG by means of a real time portable device.

Acknowledgements

The authors would like to thank the European Commission that has partially funded this work (Cardiosmart IST-2001-35073).

References

[1] Jalaleddine SMS, Hutchens CG, Strattan RD, Coberly WA. ECG Data Compression Techniques-A Unified Approach. IEEE Trans on Biomedical Eng. 1990: 37 (4): 329-341.

[2] Ljung L. System Identification-Theory for the User. Prentice Hall:1987.

[3] UNE- ENV:1065. AENOR.1999.

[4] Elena M, Quero JM, Toral SL, Tarrida CL, Segovia JA, Franquelo LG. CARDIOSMART: Intelligent Cardiology Monitoring System Using GPS/GPRS Networks. IECON 2002 Proc., Seville: 2002:4: 3419-24.

[5] Koski A. Lossless ECG encoding. Computers Methods and Programs in Biomedicine. 1997:52: 23-33.

[6] Stewart D, Dower GE, Suranyi O. An ECG compression code. Electrocardiology J. 1973: 6(2):175-6.

[7] Krishnakumar AS, Karpowicz JL, Belic N, Singer DH, Jenkins JM. Microprocessor-based data compression scheme for enhanced digital transmission of Holter recordings. Computers in Cardiology 1980: 435-7.

[8] Ahmed N, Milne PJ, Harris SG. Electrocardiographic data compression via orthogonal transforms. IEEE Trans on Biomedical Eng. 1975: 22: 484-7.

[9] Womble ME, Halliday JS, Mitter SK, Lancaster MC, Triebwasser JH. Data compression for storing and transmitting ECGs/VCGs. Proc IEEE 1977;65:702-6.

[10] Horspool RN, Windels WJ. An LZ Approach to ECG Compression. Computer-Based Medical Systems, Proc. IEEE 17th Symposium on. 1994: 71-6.

[11] Cox JR, Ripley KL. Compact digital coding of electrocardiographic data. Int. Conf. Syst. Sciences Proc VI. 1973: 333-6.

[12] http://www.physionet.org/.

Address for correspondence
Mar Elena
Electronic Engineering Department, E.S.I. U. Sevilla
Avda. Descubrimientos, s/n 41092. Spain
e-mail: marelen@us.es