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Study and Analysis of Electrocardiograms to Improve the Compression Factor and Entropy Using Linear Time-Invariant Model with Noise Filter

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Abstract: **ECG signal is the basic signal has always been chosen for the diagnosis of cardiac disorders and also been used to detect the patient's states. The electrocardiogram (ECG) is the key for observing electrical activity of the human heart and also used in disease detection purpose. For decision making purposes, some particular characteristic of ECG signal are selected as key factor which helps to take the decision and makes the diagnosis process faster and simpler. Therefore, the appropriate feature description and extraction of ECG signal becomes the most important component in cardiac health diagnostics. In this paper, some techniques for feature extraction of ECG signal have been described as signal compression is a mandatory for storing purpose in case of diagnosis. But generally from the previous established model, it has been observed that models suffer from low compression factor and high entropy. This work mainly presents some predictive technique using linear time-invariant models with noise filter to improve the errorless ECG compression factor and minimum entropy which will be beneficial for clinical research.**

Keywords — Linear Time Invariant Models, Signal Processing, ECG Signal, Analog-Digital Conversion, Entropy, Noise Filter

I. Introduction

For medical images, generally ECG signal requires less storage capacity. Nowadays, ECG monitoring devices are used often, even in a regular medical checkup also, while the medical images are recorded only is case of emergency or necessary. Electrocardiograph storage device is nothing but a necessary diagnostic device, where large amounts of data have to be stored. In telemedicine, an efficient coding of ECG signals is very much required with modern use of long-term monitoring [5], [6]. For efficient functioning of medical telemetry systems with low bitrate channels, signal compression is required and some cases it is mandatory. In case of high-resolution electrocardiogram monitoring device, it records 12-chanells ECG with 11-bit resolution with sampling rate of 1500 samples per second. Therefore, it generates over 56 MB per hour or 1360 MB per day and it maintains a constant flow to the network with of 132 kb/sec. Figure 1 and figure 2 represents the Segment of ECG signal and Digitalized segment of ECG signal respectively.

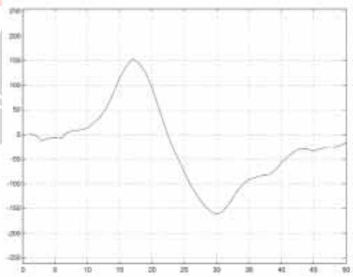

Fig 1: Segment of ECG signal

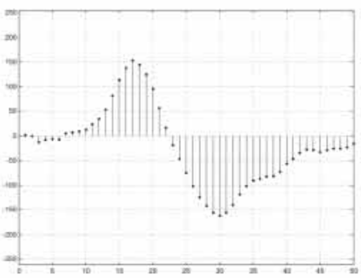

Fig 2: Digitalized segment of ECG signal

Thus the ECG signal compression is not only desirable, but also necessary. Signal compression methods are of two types called lossy and lossless [3], [12]. Lossless becomes the errorless ECG compression which is essential for storage and transmission of electrocardiographs which leads the information of current states of cardiac system. The

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purpose of ECG compression should not be used only for transmission or to store the signal with fewer bits, it is also required to preserve the bits which gives clinically significant information. In many countries, according to the law regulations [13] medical signals after lossy or erroneous compression cannot be used in diagnostics.

II. STEPS IN ECG ANALYSIS

The major steps for the analysis of the ECG signals are depicted here. Noise elimination from ECG signal is the first step to be done using noise filtering techniques. Cardiac cycle has to be detected by detecting QRS complex of ECG signal. Significant characteristic points[9] in ECG signal has been done by this detection and then formulation of characteristic feature is the second step of ECG analysis. In the third step, a Noise filter is to be connected to remove and reduce the noise components from various sources in the ECG signal[1].Cardiac cycle detection involves the detection of the QRS complex peak corresponding to each beat is the fourth step.QRS Complex detection is implemented using QRS complex detection algorithm. ECG characteristic point detection involves not only the detection of QRS complex onset and offset but also ST segment detection and T peak detection. Features formulation includes the selection of characteristic features in such way that the doctors significantly relate to the abnormalities of the patients [10]. In some cases, additional features are extracted by performing complexity analysis of the ECG signal.

III. LINEAR TIME-INVARIANT MODEL BASED APPROACH

In this work, the output of linear system is taken from the one of the leads of signal and inputs are other leads of the same signal. In this analysis, single-input single-output systems have been considered, as ECG signals are taken from test databases [15], [7]. Hence generalization to multiple-input system is very simple. Again it is known to us that, the most important class of dynamical systems is time-invariant linear systems. A System is called time-invariant if its response to a certain input signal does not varies with time and system is linear if its output response to a linear combination of inputs is the same linear combination of the output responses of the individual inputs means it obeys superposition theorem. A system is causal if the output at a certain time instant depends on the input up to that time instant only [17]. Here a system with an input signal x(n), output signal y(n), and disturbance d(n) is considered to describe the model. Figure 3 represents the dynamical system using time invariant system is given below.

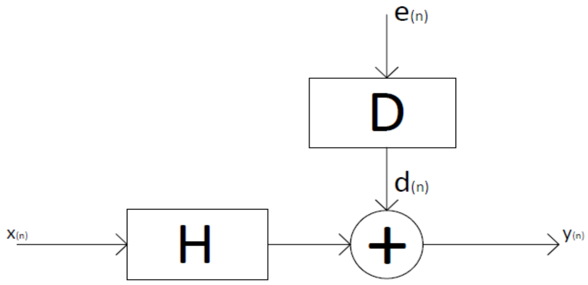

Figure 3: Represents the dynamical system using time invariant system

A system can be completely characterized by its impulse response [14]. A linear time-invariant and causal system can be described by its impulse response h(k) as given in the following equations.

y(n) = $\sum_{k=1}^{\infty} h(k)x(n-k)$ + d(n) where n = 0,1,2,3 (1)

Let the disturbance n(n) be given as follows.

d(n) = $\sum_{k=0}^{\infty} d(k)e(n-k)$ where n = 0,1,2,3 (2)

Here d(k) is the impulse response of the system generates disturbances, where e(n) is the white noise with zero mean and variance lamda. As a result the disturbance has also the zero mean[8]. So the covariance can be expressed as follows.

R_d(n) = $\lambda \sum_{k=0}^{\infty} d(k)d(k-n)$ (3)

It will be easier to introduce a shift operator P of any signal s(n) as written below.

P S(n) = S(n+1), P^1S(n) = S(n-1) (4)

Now the linear time-invariant causal system can be modeled as given in the following equations.

y(n) = H(p).x(n) + D(p).e(n) (5)

Here H(p) is the transfer function of the above stated linear time invariant system[4]. The conditional expectation of disturbance d(n) has been expressed as $\hat{d}$(n) .

$\hat{d}$(n) = $\sum_{k=0}^{\infty} d(k)e(n-k)$

$\hat{d}$(n) = [1-$D^{-1}(p)$]d(n) = $\sum_{k=0}^{\infty} -\hat{h}(n)\, d(n-k)$

$\hat{d}$(n) = [H(p)-1]d(n) (6)

The conditional expectation of output signal y(n) is given by,

$\hat{y}$(n) = H(p)x(n)+$\hat{d}$(n) (7)

From the above equation the predictor error has been formulated and given as follows.

e(n) = $D^{-1}(p)$ H(p)x(n) + $D^{-1}(p)$ y(n) (8)

From the above equation it is observed that, some portion of y(n) has not been predicted from the past data. In this work, some techniques for feature extraction of ECG signal have been described as signal compression is a mandatory for storing purpose in case of diagnosis. But generally from the previous established model, it had been observed that models suffer from low compression factor and high entropy. Predictive technique using linear time-invariant models with noise filter will be used in the next section to improve the errorless ECG compression factor and minimum entropy

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IV. ECG SIGNAL COMPRESSION AND PREDICTION

Signal compression methods are of two types called lossy and lossless. Lossless becomes the errorless ECG compression which is essential for storage and transmission of electrocardiographs which leads the information of current states of cardiac system [2], [11]. The purpose of ECG compression should not be used only for transmission or to store the signal with fewer bits, it is also required to preserve the bits which give clinically significant information. The amount of compression has been expressed with the compression ratio (CR)

$$CR = \frac{b_{original}}{b_{compression}} \qquad (9)$$

In the following figure 4 ECG signal compression technique has been depicted using a predictor and entropy encoder.

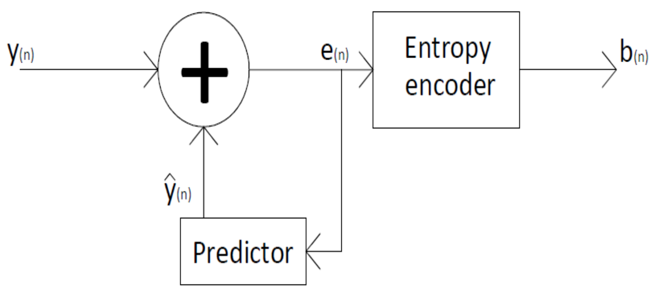

Figure 4: Represents the system for ECG compression

Possible amount of compression has been estimated based on the entropy. Now the entropy of ECG signal is defined as the average information per symbol [14] and mathematical form is given in the equation (10).

$$H = -\sum P_y \log_2 P_y \qquad (10)$$

Here Py is probability of symbol y. and it tells us what is the average number of bits required to represent a sample of ECG signal. Now figure 5 represents the system for ECG decompression given below.

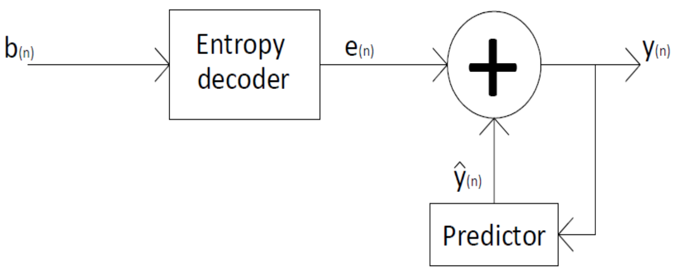

Figure 5: Represents the system for ECG decompression.

This above model describes the difference between the predicted and the original values of the current sample. For slow motion period of ECG signal, most consecutive samples will be similar, but the difference will be greater when the motion increases. Here it is assumed that[16] ,entropy coding of ECG signal prediction error will achieve better compression ratio then entropy coding of original ECG signal.

V. AR MODEL FOR ECG COMPRESSION

The AR model was developed for a single-output system where an output signal y(n) in the previous research work and can be written as follows.

$$y(n)+a_1\, y(n-1)+\ldots\ldots+ a_n\, y(n-n_a) = y_n \sum_{k=1}^{n_a} a_k\, y(n-k)$$

$$e(n) = y(n)+\left[\sum_{k=1}^{n_a} a_k\, P^{-k}\right]y(n) \ldots\ldots\ldots(11)$$

$$\text{Where } A(p)=1+ a_1 P^{-1} + \ldots\ldots+a_{n_a} P^{-n_a} \qquad (12)$$

The parameter of AR model vector has the form given below.

$$\emptyset = [a_1, a_2, \ldots\ldots \ldots.., a_{n_a}]^{\tau} \qquad (13)$$

The predictor of AR model can be expressed by difference equation as follows considering thr past knowledge.

$$\hat{y}(n) = [1-A(p)]y(n) \qquad (14)$$

State vector model of AR model can be written in the form of difference parameter.

$$\emptyset(n) = [-y(n-1) - y(n-n_a)]^{\tau} \qquad (15)$$

As the calculation of the predictor is critical and past data does not depend on the parameter vector, predictor leads linear regression. Though it is a disadvantage of AR model, yet is used till now for some typical case. The problem can be overcome in our proposed model using noise filter.

VI. OUR PROPOSED MODEL FOR ECG COMPRESSION

In our proposed design AR model has been modified using a noise filter .As a result, predictor does not lead linear regression. The first step in noise filtering deals with the elimination of most commonly present noise such as the AC power noise. Baseline noise is also important noise which falls in the frequency band of 10Hz whereas AC power noise is in the region of 50 Hz and its harmonics. According to the recommendations made by American Heart Association for ECG recordings, in the lower frequency region, the frequency components above 0.5 Hz should not be removed. Hence the cutoff frequency is chosen as 0.5 Hz to remove the baseline noise. In a ECG signal, the high frequency component is the QRS complex is about 20 Hz. To remove the high frequency noises and the power noise the cut off frequency is chosen from the previous research work as 21 Hz. The actual and filtered output for Class A and Class C ECG signal are taken from recorded ECG signal. Transfer function of the second order low pass filter in discrete domain and the difference equation are given by

$$H(z) = \left(\frac{1-z^{-6}}{1-z^{-1}}\right)^2 \qquad (16)$$

$$y(nT) = 2y(nT-T)-y(nT-2T)+x(nT)-2x(nT-6T)+x(nT-12T) \qquad (17)$$

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Again the transfer function of the second order high pass filter in discrete domain and its difference equation can be written as follows.

$H(z) = \frac{1-z^{-32}}{1-z^{-1}}$ (18)

$y(nT) = y(nT-T)+x(nT)-x(nT-32T)$ (19)

After passing through a noise filter AR model is applied to get better result. Output signal y(n) of the new proposed model can be presented by linear difference equation given below.

$y(n)+a_1\, y(n-1)+\ldots\ldots+ a_{n_a}\, y(n-n_a) = e(n)+ c_1 e(n-1)+\ldots\ldots+ c_{n_a}\, e(n-n_a)$ (20)

The difference equation of predictor is given by

$\hat{y}(n|\emptyset) = [1-\frac{A(p)}{C(p)}]\ y(n)$ (21)

Here the prediction error of output signal is reduced and given by the following equation.

$e(n, \emptyset) = \frac{A(p)}{C(p)}\ .y(n)$ (22)

As in the calculation of the predictor, past data depends on the parameter vector, predictor deals with pseudo-linear regression but gives better compression ratio.

VII. COMPARATIVE STUDY BASED ON SIMULATION RESULT

In this paper, a simple AR models has been described which is nothing but a previous research work. After that our proposed model has been explained which uses a noise eliminating filter along with previously described AR model .It has been observed that, the proposed model gives better compression ratio and tabulated in table 1.

	Hmin(b/sym)	Hmax(b/sym)	CRmin	CRmax
AR Model	3.37	5.70	2.11	3.56
Propose d Model	3.34	5.59	2.13	3.52

Table1. Results of ECG signal prediction

Figure 5 and Figure 6 depicted below represents the difference based on simulation result of AR model and the modified AR model.

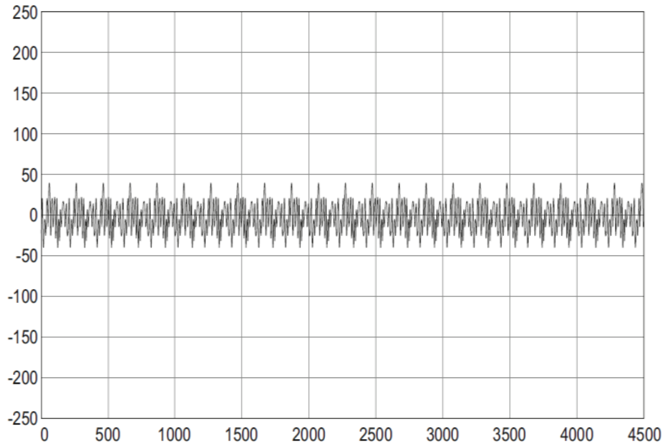

Fig 6: ECG signal prediction error in AR Model

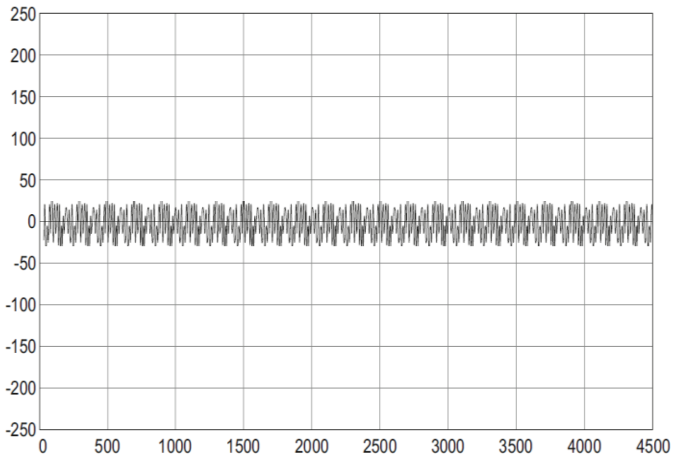

Fig 7: ECG signal prediction error in modified AR Model

It is very clear from the simulation result that compression factor has been improved and error is also less after compression in our proposed model as noise filter is introduced.

VIII. CONCLUSION

This work represents some predictive techniques for errorless ECG compression. Control theory based approach describes different models which have been used for data compression purpose in previous research work. Using these models ECG signals are getting compressed with minimum error means compression factor has been improved with our proposed model. Here linear time-invariant models are used to describe some predictive technique which deals with the feature extraction of ECG signal. Based on mathematical results, it can be concluded that, instead of using only AR models, if a noise filter is connected along with the model, entropy is minimized and iteration for linear regression is not required. After prediction, prediction error signal has also been depicted by doing simulation in our proposed design. It is observed from the simulation result, compression factor has been improved and error is also less after compression in our proposed model as noise filter is introduced. Resolution of 10 bits per sample and sampling rate of 230 samples per second offer good compromise between storage capacity and quality.

REFERENCES

[1] Alste, J.A.V.,and Schilder, T.S.‘Removal of base-line wander and power line interference from the ECG by an efficient FIR filter with a reduced number of taps’, IEEE Trans. Biomed. Eng., 32, pp. 1052–1060.

[2] Bajiæ D. ECG standards?, MEDNET 2001, The 6th World Congress on the Internet in Medicine,Udine, Italy, 29 Nov - 2Dec 2001.

[3] Duda K, Turcza P, Zielinski TP. Lossless ECG Compression with Lifting Wavelet Transform, IEEE

 DOI : 10.18231/2454-9150.2019.0387

Instrumentation and Measurement Technology Conference, Budapest, Hungary, May 21-23, 2010. p. 640-4.

[4] Despotovic M, ®igon N, Bajiæ D. ECG signal compression techniques. Annals of the Academy of Studenica 2010;(4).

[5] Elaine Marieb, Human Anatomy and Physiology, 3rd ed. Pearson Benjamin Cummings; 1995. p. 615-33.

[6] Friesen, G.M., Thomas, C.J., Jadallah, M.A., Yates, S.L., Quint, S.R., and Nagle, H.T. (1990): 'A comparison of noise sensitivity of 9 QRS detection algorithms', IEEE Trans. Biomed. Eng.

[7] Hamilton, P.S., and Tompkins, W.J. (1986): 'Quantitative investigation of QRS detection rules using the MIT/BIH arrhythmias database', IEEE Trans. Biomed. Eng., 33, pp. 1157–1165.

[8] Huffman DA. A Method for the Construction of Minimum-Redundancy Codes, Proceedings of the I.R.E., 40 (September 1952). p. 1098-101.

[9] Jalaleddine SMS, Hutchens CG, Strattan RD, Coberly WA. ECG data compression techniques – a unified approach. IEEE Transactions on Biomedical Engineering 1990;37(4).

[10] Kenneth, P.B. (1982): 'Rule based learning for more accurate ECG analysis', IEEE Trans. Pattern analysis and Machine intelligence, 4, pp. 369–379.

[11] Lin, P.K., and Chang, W.H. (1997): 'A technique for automated arrhythmia ndetection of holter ECG', In Proceedings of Engineering in Medicine and Biology, 35, pp. 626–631.

[12] Mervin, J.G., and Goldschalager, N. (1989): 'Principles of clinical Electrocardiography', Appleton Lange.

[13] Pan, J., and Tompkins, W.J. (1985): 'A real-time QRS detection algorithm',IEEE Trans. Biomed. Eng., 32, pp. 230–236.

[14] Rissanen JJ, Langdon GC. Arithmetic coding, IBM

Journal of Research and Development 1979.

[15] Shahabi C, Ortega A, Kolahdouzan MR. A Comparison Of Different Haptic Compression Techniques,Integrated Media Systems Center, University of Southern California.

[16] Thakor, N.V., Webster, J.G., and Tompkins, W.J. (1984): 'Estimation of QRS complex power spectra for design of a QRS filter', IEEE Trans. Biomed. Eng., BME-31 (11), pp. 702–706.

[17] Williams, J.L.,Benmel, J.H.V., Zywietz, C. (1986): 'Computer ECG Analysis',Elseiver Science Publishers.

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