EFFICIENT LOSSLESS COMPRESSION SCHEME FOR MULTI-CHANNEL ECG SIGNAL

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ABSTRACT

Electrocardiogram (ECG) is the recording of the heart electrical activity and used to diagnose heart disease nowadays. The diagnosis requires a large amount of time for acquiring enough multi-channel data normally. Thus storage and transmission of 12 lead ECG data will result in massive cost. In this work, we propose a multi-channel ECG lossless compression which uses the adaptive linear prediction for intra and inter channel decorrelation. The proposed technique is based on the adaptive Golomb-Rice codec for entropy coding with adaptive linear prediction. Thus the coefficient of linear prediction and Golomb-Rice codec will make self-adjustment during the process. Finally we evaluate the proposed algorithm with MIT-BIH Arrhythmia database for single-channel compression, and PTB database for multi-channel compression.

Index Terms— Lossless compression; multi-channel ECG signal; telemedicine; Golomb-Rice codec; linear prediction

1. INTRODUCTION

In recent years, cardiovascular disease have become an important cause of death. Monitoring electrocardiogram is the most used method for diagnosis of cardiovascular disease. Multi-channel electrocardiogram (ECG) provides full information of heart electrical activity simultaneously for a better diagnosis of every cardiovascular conditions. In reality, multi-channel ECG data will be recorded continuously for hours, accompanied by a huge amount of data. Furthermore, the rise of wearable devices starts a new generation of telemedicine. Nowadays ECG recorder is not only used in hospital but also in mobile device. The large cost of storage and transmission loading will be a challenge for this issue.

Most ECG compression technique is proposed with lossy mode to gain better compression rate. Although data distortion has been controlled in acceptable range, it may cause some misdiagnosis while the diagnosis may occur. Consequently lossless ECG data compression is proposed to prevent any misunderstanding of judgement. This technique can effectively reduce the amount of bits that necessary to store and transmission loading while maintaining data quality without any distortion.

In this work, we propose a multichannel ECG compression technique which exploits intra-channel and inter channel correlation to remove redundancy in lossless mode. We use the encoder of "Reduced lead ECG" [1,2] as multi-channel linear predictor for reduce inter-channel redundancy. The adaptive linear prediction technique is also used with exponential weighting technique [3] for reduce intra-channel redundancy. The entropy coding consists of self-adjusted Golomb-Rice codec which means the parameter of Golomb-Rice codec will self-adjust based on forward entropy. Finally, we evaluate the performance by calculating the compression ratio (CR).

The paper is organized as follows: first we introduce the overview of lossless encoder architecture in Section 2. Section 3 contains the experimental result for single/multi-channel ECG compression and the comparison with other methods. Finally, the conclusions are discussed in Section 4.

2. LOSSLESS ECG COMPRESSION

The proposed lossless ECG compression scheme consists of three elements. Original ECG data is fed into multi-channel linear prediction unit (MLP) to create the approximation of different ECG channels. The generated ECG from MLP are subtracted by original ECG channel respective to form a set of residual each channel. The residual channels are fed into adaptive linear prediction unit (LP) to reduce the intra-channel redundancy. To improve the compression efficiency, we propose a self-adjusted Golomb-Rice codec. The proposed compression encoding scheme block diagram is shown in Fig.1.

2.1. Multi-channel linear prediction

The main challenge in multi-channel ECG compression is the decorrelation of the ECG channels. It can be achieved by using multi-channel linear prediction technique to remove the redundancy between channels. Multi-channel linear prediction can be implemented based on inter-channel correlation over a large sample of patient for generalized or created individual from patient's data for high prediction accuracy. Currently 12 lead channels are extracted for usage.

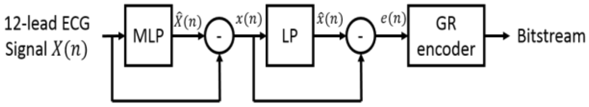


Fig. 1. Encoding scheme block diagram

The redundancy between 12 lead ECG signal can be removed by choosing reference set of ECG channels and be predicted by the rest of ECG channels.

$$\hat{X}_{p,j}(n) = \sum_{i=1}^{k} h_{j,i}\, X_{r,i}(n) \tag{1}$$

Where $\hat{X}_{p,j}(n)$ is predict value of n sample in predict channel j, $X_{r,i}(n)$ is n sample of reference channel i and $h_{j,i}$ is the predictor coefficient.

As mentioned both generalized and patient specific multi-channel linear prediction exist choose generalized mode in order to fit every condition of ECG data. In this work, we introduce the result of [2] as multi-channel linear predictor. Reduced lead ECG is by used of few leads than traditional 12-lead ECG. Therefore, it can be more convenient in the situation of long-term ECG monitoring. The main application of reduced lead ECG is converted with few leads ECG signal, meanwhile the standard 12-lead ECG signals are the coefficient of linear predictor generated by using some linear regression. We choose 4 lead of ECG, I, II, V1, V5, as reference lead and use the result of reduced-lead ECG to predict the rest, III, aVR, aVL, aVF, V2, V3, V4, V6 by following equation (2) to (9), where (6) to (9) are based on [2].

$$\mathrm{III} = \mathrm{II} - \mathrm{I} \tag{2}$$

$$\mathrm{aVR} = \frac{-(\mathrm{I} + \mathrm{II})}{2} \tag{3}$$

$$\mathrm{aVF} = \frac{(\mathrm{II} + \mathrm{III})}{2} \tag{4}$$

$$\mathrm{aVL} = \frac{(\mathrm{I} - \mathrm{III})}{2} \tag{5}$$

$$\begin{aligned} \mathrm{V2} = {} & (0.887330 * \mathrm{I}) - (0.09116 * \mathrm{II}) \\ & +(1.57862 * \mathrm{V1}) + (0.230214 * \mathrm{V5}) \end{aligned} \tag{6}$$

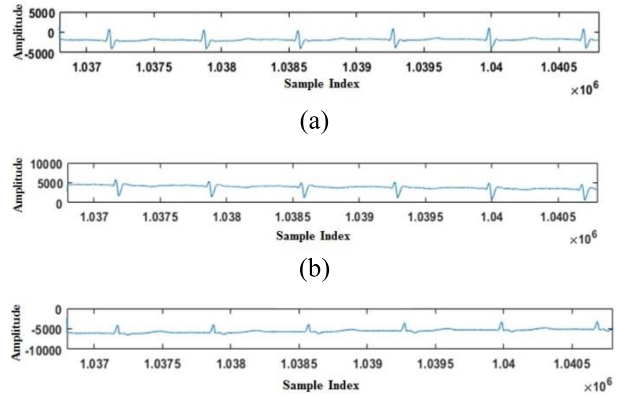
$$\begin{aligned} \mathrm{V3} = {} & (0.245068 * \mathrm{I}) + (0.447773 * \mathrm{II}) \\ & +(1.14726 * \mathrm{V1}) + (0.609744 * \mathrm{V5}) \end{aligned} \tag{7}$$

$$\begin{aligned} \mathrm{V4} = {} & (0.111111 * \mathrm{I}) - (0.064849 * \mathrm{II}) \\ & +(1.57862 * \mathrm{V1}) + (0.230214 * \mathrm{V5}) \end{aligned} \tag{8}$$

$$\begin{aligned} \mathrm{V6} = {} & (0.202721 * \mathrm{I}) - (0.038811 * \mathrm{II}) \\ & -(0.176913 * \mathrm{V1}) + (0.59492 * \mathrm{V5}) \end{aligned} \tag{9}$$

The result of predict channel is similar to the original channel as shown in Fig.2. Finally, we subtract the original ECG channel with predict channel to form the redundancy set of predict channel:

$$x_p(n) = X_p(n) - \hat{X}_p(n) \tag{10}$$



(a)

(b)

(c)

Fig. 2. Predict signal of V4; (a)Original signal (b) Predict signal using MLP (c)Redundency Set

Where $x_p(n)$ is the predict error of n sample and $X_p(n)$ is n sample of original predict channel.

2.2. Adaptive linear prediction

In ECG signal, there are some steep states such as P, Q, R, S, T wave. These waves will cause high prediction error. To reduce the overall error, we use different predictors in different condition to promote the efficiency. We propose an adaptive linear prediction based on fuzzy theory, and exponential weighting technique to reduce the prediction error as much as possible. Linear prediction is used to estimate the current sample from the past sample as following.

$$\hat{x}(n) = \sum\nolimits_{i=1}^{m} a_i x(n-i) \tag{11}$$

Where $\hat{x}(n)$ is a prediction value of $x(n)$, m is the order of predictor and a_i is coefficient. We use the first order linear prediction which have better performance at flat region. The second and fourth order linear prediction with exponential weighting technique for other regions are used to gain better performance at steep region. The different order of linear prediction is described as following.

$$\text{1st order: } \hat{x}_i(\mathrm{n}) = x_i(\mathrm{n}-1) \tag{12}$$

$$\text{2nd order: } \hat{x}_i(\mathrm{n}) = 2x_i(\mathrm{n}-1) - x_i(\mathrm{n}-2) \tag{13}$$

$$\begin{aligned} \text{4th order: } \hat{x}_i(\mathrm{n}) = {} & 4x_i(\mathrm{n}-1) - 6x_i(\mathrm{n}-2) \\ & +4x_i(\mathrm{n}-3) - x_i(\mathrm{n}-4) \end{aligned} \tag{14}$$

First, we use the correlation between the pass sample to estimate where the current sample is. It is calculated by the difference between two samples. If the difference between $x_i(\mathrm{n}-1)$ and $x_i(n-2)$ and the difference between $x_i(\mathrm{n}-3)$ and $x_i(\mathrm{n}-2)$ are both less than threshold, we assume the current sample is located at flat region. Once the sample is

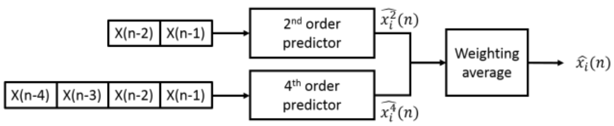


Fig. 3. Exponential weighting scheme

located at flat region, first order linear prediction will be applied. Otherwise 2nd and 4th order linear prediction with exponential weighting technique will be applied.
For steep region, exponential weighting technique is applied. The scheme of exponential weighting is shown in Fig.3. The final predicted value of sample is a weighting average of outputs of 2nd and 4th order linear predictor.

$$\omega_r(\mathrm{n}) = 2^{C-\overline{e_r}(n)} \tag{15}$$

$$\widehat{x_i}(n) = \frac{\omega_2(n)\widehat{x_i^2} + \omega_4(n)\widehat{x_i^4}}{\omega_2 + \omega_4} \tag{16}$$

Where C is a constant and $\overline{e_r}(n)$ denoted the average predict error of a predictor at time n. $\omega_r(\mathrm{n})$ is a weight of r order predictor that will decay base on $\overline{e_r}(n)$. Since the ECG signal is a non-linear system referring to its predict error, we average the pass three predict errors as $\overline{e_r}(n)$.
To form the final residual set, we subtract the output of MLP with output of linear prediction as following:

$$\mathrm{e(n)} = \mathrm{x(n)} - \hat{x}(n) \tag{17}$$

where e(n) denoted predict error which feed into entropy coding unit. Since ECG does not have deterministic properties, we take advantage of the trend of the first four signals to simplify uncertainty into two situations: flat and non-flat, and match the corresponding predictor to solve the problem.

2.3. Golomb-Rice Codec

Golomb coding depends on the entropy and geometric distribution. In particular, a Rice code corresponds to a Golomb code in which the parameter is a power of two. Since the value of ECG data is tend to Laplace distribution as shown in Fig.4, Golomb code will be quite suitable. However, since the predict error may be negative value, it is necessary to translate the negative value to positive value. The mapping function is shown in (18), and the predicted value e(n) will be rounded to the integer.

$$E(n) = \begin{cases} 2e(n), & e(n) \geq 0 \\ 2|e(n)| - 1, & e(n) < 0 \end{cases} \tag{18}$$

Originally one bit for sign is recorded directly. We use the mapping method which will save one bit while the absolute value of negative value is equal to power of two. Thus it can gain a better compression performance.

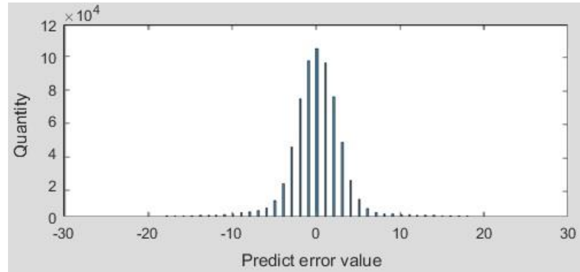


Fig. 4. Distribution of predict error

The Golomb-Rice code consists of the value of quotient and remainder, as shown in (19).

$$\begin{cases} quotient\text{:} \dfrac{E(n)}{2^k} \\ remiander\text{:} E(n) mod 2^k \end{cases} \tag{19}$$

Where k is positive parameter and it represents number of bits for remainder, and $E(n)$ is the predict error after mapping. The unary and binary codes are used to encode quotient and remainder respectively.
Since the efficiency of Golomb-Rice code is sensitive to k parameter, this work propose a self-adaptive Golomb-Rice code that will adjust k parameter based on the pass three predict error. The concept of this method is that the predict error in neighbor will locate nearby in distribution. The forward three predict errors are applied to determine k parameter by mean absolute error (MAE) shown in (20) and (21). This method can optimize the k parameter to present the predict error without any side information required for decoder.

$$\mathrm{MAE(E(n))} = \frac{\sum_{n=1}^{N}|E(n)|}{N} \tag{20}$$

$$\mathrm{k} = \log_2 MAE(E) \tag{21}$$

3. PERFORMANCE EVALUATION

The MIT-BIH Arrhythmia database and MIT-BIH PTB diagnostic database were used to evaluate the performance of the proposed work. With two ambulatory channels, the MIT-BIH Arrhythmia database was used as a benchmark for 48 half-hour ECG recordings. In the 10 mV range the sampling frequency of data is in 11-bit resolution at 360 Hz. PTB database contains the recordings of 249 subjects with total 548 ECG recording. The ECG recordings contain 12 lead ECG data with 16-bit resolution and sample rate 1000Hz. Most of records are recorded for 2 minutes.
In order to evaluate the performance in lossless mode, we calculated the compression ratio (CR).

$$\text{Compression ratio} = \frac{S_o}{S_c} \tag{22}$$

Where S_o is the bits used in original data, and S_c is the number of bits used after compression.

Table 1. Performance comparison with other algorithm in MIT-BIH Arrhythmia database

Ref	Technique	Avg. CR
[4]	Delta coding + zero run-length encoding	2.11
[5]	Adaptive linear prediction + two stage Huffman coding	2.53
[6]	Adaptive region prediction + variable length coding	2.67
[7]	Peak detection + backward difference Huffman coding	2.64
proposed	Adaptive linear prediction + Golomb-Rice coding	2.89

Table 2. Performance comparison with other algorithm in PTB database

Ref	Technique	Avg CR
[10]	MPEG4-ALS	3.22
proposed	MLP + LP + Golomb-Rice coding	3.98

First, we evaluate the performance for single-channel compression with MIT-BIH Arrhythmia database. Since this evaluation was limited in single channel, the performance only relies on the linear prediction and Golomb-Rice code. Table 1 shows the comparison between the proposed method and relative techniques. In [4], a traditional delta coding achieved a 2.11 CR. However, delta coding does not minimize the predict error. [5] used Huffman coding as its entropy coding but it required additional memory to save Huffman table. In the proposed algorithm, it can improve CR about 9% over [6] and [7]. Although [8]-[9] can offer better compression efficiency, [8] is hard to applied since there are different kinds of noise during data acquiring. The result of cluster might be getting worse. [9] used the neural network-based method. However it required strong hardware to support the large computation.

Next, we evaluate the performance for multi-channel compression with MIT-BIH PTB database. Table 2 shows the comparison between the proposed method and relative techniques. [10] used MPEG4-ALS for multi-channel ECG compression and it can achieve CR 3.22. However this MPEG-based codec is a complex framework. We also evaluate the effect of MLP unit by PTB database with/without MLP unit. With MLP unit, the compression ratio can improve 33%.

4. CONCLUSION

This paper proposed a multi-channel lossless ECG compression algorithm. We use multi-channel linear prediction with exponential weighting technique, and self-adaptive Golomb-Rice coding. Our self-adaptive Golomb-Rice code will adjust k parameter during the process based on the distribution of predict error. The proposed method shows better performance compared to the reported methods.

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