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An Efficient ECG Lossless Compression System for Embedded Platforms With Telemedicine Applications

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ABSTRACT This paper presents a method for wireless ECG compression and zero lossless decompression using a combination of three different techniques in order to increase storage space while reducing transmission time. The first technique used in the proposed algorithm is an adaptive linear prediction; it achieves high sensitivity and positive prediction. The second technique is content-adaptive Golomb–Rice coding, used with a window size to encode the residual of prediction error. The third technique is the use of a suitable packing format; this enables the real-time decoding process. The proposed algorithm is evaluated and verified using over 48 recordings from the MIT-BIH arrhythmia database, and it shown to be able to achieve a lossless bit compression rate of 2.83× in Lead V1 and 2.77× in Lead V2. The proposed algorithm shows better performance results in comparison to previous lossless ECG compression studies in real time; it can be used in data transmission methods for superior biomedical signals for bounded bandwidth across e-health devices. The overall compression system is also built with an ARM M4 processor, which ensures high accuracy performance and consistent results in the timing operation of the system.

INDEX TERMS Electro-cardiogram (ECG), Golomb-Rice coding, lossless data compression, wearable devices, healthcare monitoring, telemedicine.

I. INTRODUCTION

Cardiovascular diseases (CD) have become the top cause of death globally in recent years, responsible for over 31% of all global deaths annually [1]. Reading electrocardiogram (ECG) signal is the most commonly used method to monitor heartbeat. This biomedical signal is widely used in medicine as a screening tool for cardiac disease diagnosis. It has various components such as waves, segments and intervals. A typical ECG signal is shown in Fig. 1 [2].

The precautionary benefits of ECG data are limited due to their low availability. Long-term ECG recording is often carried out with patients admitted with cardiac problems. ECG can also be recorded continuously for 24-48 hours using monitors for mobile patients [3]. Thus, a large amount of data is collected using continuous ECG monitoring systems over such periods. In order to reduce the amount of data, a real-time data compression algorithm which can save storage space is needed.

Three types of compression techniques are used on ECG data [4] (Fig. 2).

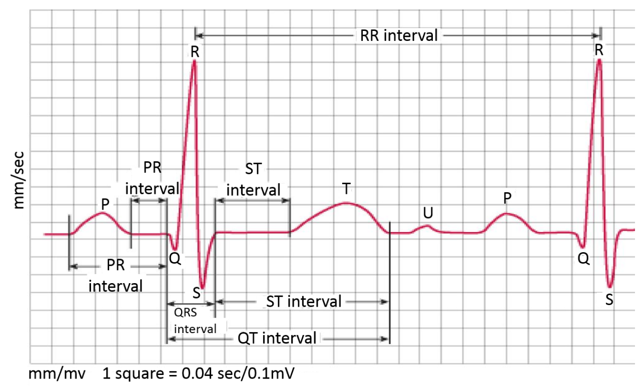

FIGURE 1. **A period of typical ECG signal [2].**

1) The direct data method uses the data in time domain for compression. Several well-known direct data techniques are used, including delta pulse code modulation (DPCM) [5], [6], turning point (TP) [7], amplitude zone time epoch

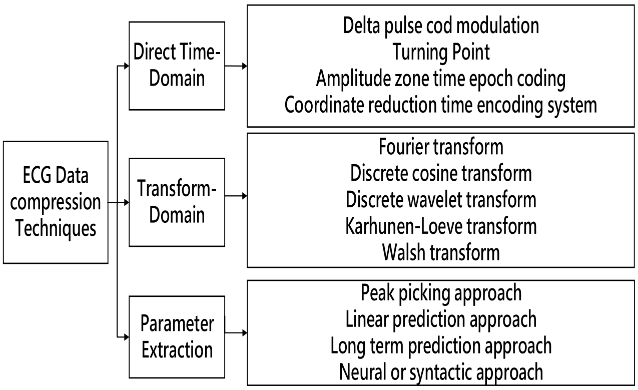

FIGURE 2. The overview of ECG compression technique.

coding (AZTEC) [8], [9], coordinate reduction time encoding system (CORTES) [10], the delta algorithm and Fan algorithm [11].

2) The transformed method converts the time domain into a frequency domain; the key idea is based on energy re-distribution. Traditionally, Fourier transform, Fourier descriptor [12], Karhunen-Loeve transform (KLT) [13], Discrete cosine transform (DCT) [14], [15] and Wavelet transform [16], [17] have all been widely used. Some new ideas, such as compressed sensing, are still based on this method [18].

3) The parameter extraction method extracts the dominant features from the raw signal; others developed include the peak picking and prediction method [19], and the neural-based or syntactic methods [20].

In general, the compression method applied in the ECG signal includes lossless compression and lossy compression. Although lossy compression techniques deliver greater compression performance, they are not accepted by medical regulatory bodies. In lossless systems, the original ECG signal can be precisely decoded without any loss and the accuracy for diagnosis of cardiac disease is improved; as a result, these systems are more emphasized in biomedical signal use.

Lossless compression techniques inherently have lower compression ratios compared to lossy compression. A classical ECG lossless compression algorithm consists of a prediction element and an entropy coding element, as shown in Fig. 3. Linear or regular prediction is one of the methods used for one dimensional ECG signal prediction techniques [21].

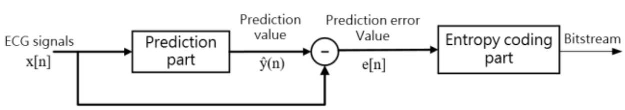

FIGURE 3. Block diagram of basic lossless compression for ECG signal.

Chua *et al.* reported a discrete pulse code modulation (PCM) for linear prediction [22], while Deepu and Lian proposed a forward prediction-based approach for linear prediction. These prediction techniques provide a simple way to reduce the prediction errors of a signal. Entropy coding is an essential step in ECG compression, as in Huffman coding [23]–[25], Golomb-Rice coding [21], and Prediction error coding [22], [25]. These entropy coding techniques allow for an efficient and low-complexity lossless compression method.

This study proposes an efficient ECG compression algorithm for telemedicine application. The primary technique of the proposed algorithm consists of two elements. The adaptive prediction element based on forward samples, in order to reduce the redundancy within the original data. It can improve the predictive accuracy and thereby enhance the compression rate. The entropy coding element consists of a window size based on content-adaptive Golomb-Rice, and used to compress ECG data.

The remainder of this paper is arranged as follows: Section II provides an overview of the proposed ECG lossless compression technique. Section III describes the wearable ECG monitoring system platform design. Section IV presents the implementation results and shows verification with the MIT-BIH database. Comparisons with other works are also provided. Conclusions are discussed in Section V.

II. LOSSLESS ECG COMPRESSION

Fig. 3 shows a block diagram of the proposed lossless ECG compression scheme. A prediction value, y ^(n), is used to derive the present value from past samples. Thus the prediction error value, e(n), is produced by the present value and prediction value, defined as:

$$\mathrm{e}\,(n) = y\,(n) - \hat{y}\,(n) \tag{1}$$

where $\hat{y}(n)$ is the prediction value, and $y(n)$ is the present value of the ECG input data.

To improve the compression performance for the ECG signal, this study proposes an effective adaptive linear predictor and a context-adaptive Golomb-Rice code with a window size to increase the compression ratio. Prediction error value is utilized in Golomb rice code and is used to calculate k—parameter also. The proposed compression encoding and decoding block diagram is shown in Fig. 4.

A. ADAPTIVE LINEAR PREDICTION

ECG signals have numerous states with steep amplitude variations, such as QRS waves, P waves and T waves. These waves may result in a higher prediction error. In order to reduce the complete error, the predictor with the best prediction can minimize the prediction error and promote the accuracy of the predictions. This study proposes an adaptive linear predictor technique according to the fuzzy decision theory [33] to reduce the prediction error as far as possible. Commonly, the forward linear prediction is used to estimate the current sample y(n) of the ECG signal in these approaches from its past m samples:

$$\hat{y}(n) = \sum\nolimits_{l=1}^{m} h^{k} y(n-l) \tag{2}$$

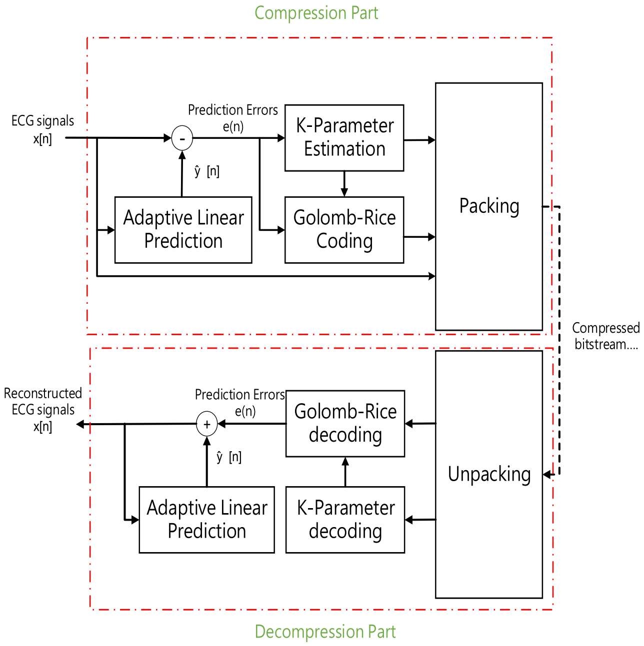

FIGURE 4. **Lossless compression-decompression scheme.**

where $\hat{y}(n)$ is a prediction assessment of $y(n)$, and h^k is the predictor coefficients.

The proposed method uses the forward four samples to estimate the prediction value. There are five parameters: *D1_2*, *D1_3*, *D2_3*, *D3_4* and *'dir'*. The proposed method determines the current prediction value according to the past values. The *'dir'* parameter determines whether the slope direction of these forward samples is the same or not. If samples, being used for parameter calculation, have same slope direction, then it's value is 1 else it is assigned 0. If current sample value is greater than previous sample value, then slope is same as values are rising and rising. But if current sample value becomes smaller than previous one then slope is different as earlier slope was rising due to rising sample values but now slope will fall down suddenly as previous sample value is greater than current sample value. The relations of the four past samples are shown in Fig. 5. *D1_2(n)* can be obtained by the previous value $y(n-1)$ minus the previous value $y(n-2)$, *D1_3(n)* can be obtained by the previous value $y(n-1)$ minus the previous value $y(n-3)$, *D2_3(n)* can be obtained by the previous value *y(n-2)* minus the previous value $y(n-3)$, and *D3_4(n)* can be obtained by the previous value*y(n-3)* minus the previous value $y(n-4)$. The equations are given in (3) to (6):

$$D1\_2\,(n) = y\,(n-1) - y\,(n-2) \tag{3}$$
$$D1\_3\,(n) = y\,(n-1) - y\,(n-3) \tag{4}$$
$$D2\_3\,(n) = y\,(n-2) - y\,(n-3) \tag{5}$$
$$D3\_4\,(n) = y\,(n-3) - y\,(n-4) \tag{6}$$

Considering the characteristics of the ECG signal, this study uses a modest coefficient with differential predictors, which have low complexity computation and good performance for evaluating prediction value. Three order differential predictors are proposed as (7) to (9):

$$Fun1 : \hat{y}\,(n) = y\,(n-1) \tag{7}$$
$$Fun2 : \hat{y}\,(n) = 2y\,(n-1) - y\,(n-2) \tag{8}$$
$$Fun3 : \hat{y}\,(n) = 3y\,(n-1) - 3y\,(n-2) + y\,(n-3) \tag{9}$$

Due to the time-based variation of the ECG signal, the predictor will be chosen from these three differential functions for numerous sections of the ECG signal, and the proper prediction will be adaptively chosen. Here, a threshold, THR, is set to determine whether the variation of the wave is high or low. For flat region, Fun1 will be selected as it is first order function and first order function has better accuracy for prediction value. For slope region, Fun2 will be selected which is a 2nd order function. For peak region sample, third order predictor will be selected which is Fun3. Third order predictors are better for finding prediction value for peak sample. The adaptive linear prediction with fuzzy decision technique is shown in Fig. 6.

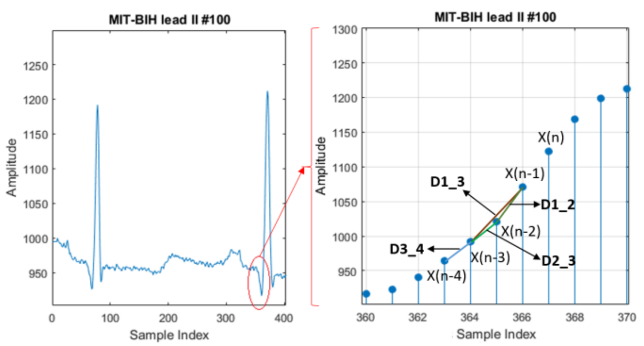

FIGURE 5. **The relation of the forward four samples.**

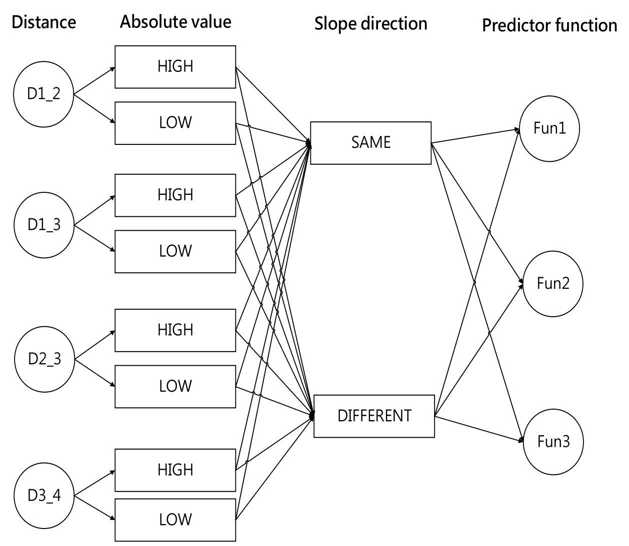

FIGURE 6. **Adaptive linear prediction with Fuzzy decision theory.**

The technique can be divided into four steps. First, the past four values $y(n-1)$, $y(n-2)$, $y(n-3)$ and $y(n-4)$ are stored for sample $y(n)$. These four values represents the values of four samples which are in the data before the current value $y(n)$. Second, the high or low state of the threshold value determines the absolute values of *D1_2, D1_3, D2_3* and *D3_4*. Third, the slope direction of *D1_2, D1_3, D2_3* and *D3_4* is classified as having either the same or different directions. Finally, one of the three predictor functions is selected using fuzzy decision theory based on the three functions: distance, absolute value and slope direction.

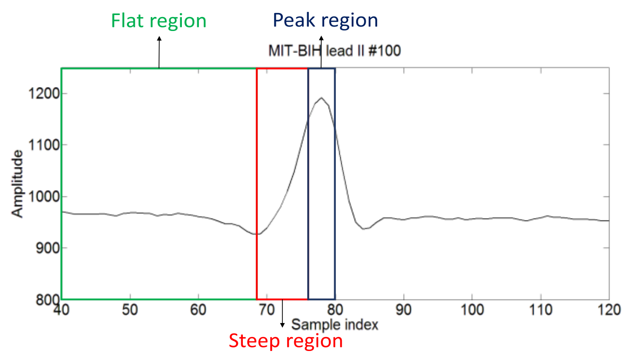

FIGURE 7. The segment of ECG signal.

Each wave segment of the ECG signal has a suitable prediction function, as shown in Fig. 7. For segments with large amplitude variation, such as the QRS wave region, Fun3 can provide better prediction performance than the others can. On the other hand, for segments with small amplitude variation, such as flat regions, Fun1 can perform better. A detailed flow chart of how to select the prediction value is shown in Fig. 8.

The prediction performance of the combination of several types of predictor is estimated for the prediction error as illustrated in Fig. 9. For the signal with steep amplitude variations such as QRS region, it will result in a higher prediction error. Fig. 9(a) represents the original ECG data in the MIT/BIH arrhythmia database #100. Fig. 9(b) shows the redundancies between consecutive samples using delta coding method [21]. Another method, short term linear prediction coding, is also compared and illustrated in Fig. 9(c). This figure is completely extracted from the result in [22]. Finally Fig. 9(d) shows the prediction error using the proposed adaptively linear prediction technique, which can yield the lower prediction error for all segments of the ECG signal. Through this adaptive linear prediction technique, the prediction accuracy can be verified, while the prediction error of frequency distribution inclines to the center, and the peak value is near zero.

B. LOSSLESS DATA COMPRESSION TECHNIQUE

Entropy coding is a vital coding technique used in data compression, and represents binary bits, regularly appearing patterns and infrequent binary bits. Huffman coding,

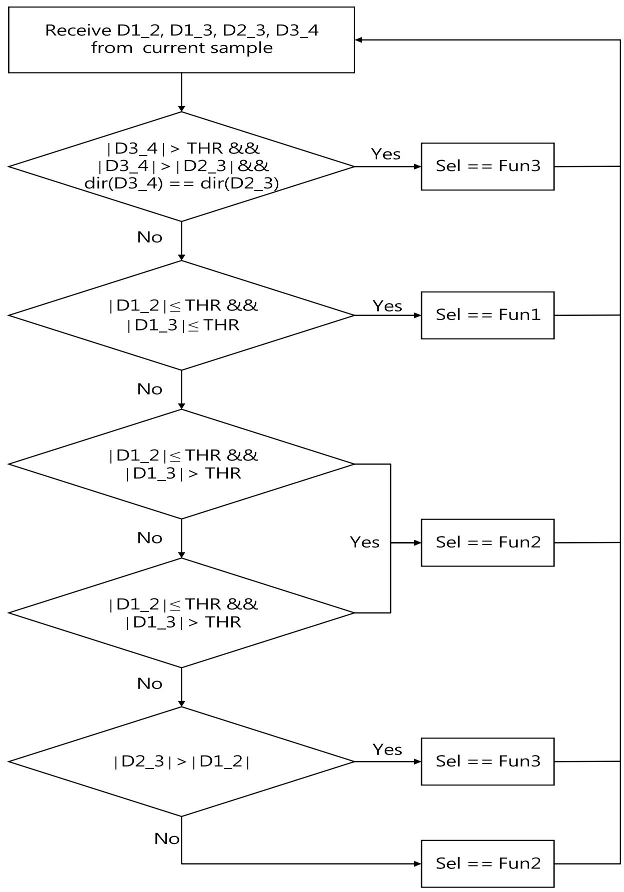

FIGURE 8. The selection of prediction value flow chart.

arithmetic coding, run length coding and Golomb coding are famous lossless entropy coding techniques, although Huffman and arithmetic codes strictly follow the input data and need an adequate memory structure to perfect the data of the input symbol probabilities. Based on [26] and [27], this work discusses in detail the idea of encoding compressive sensing measurements by means of a low-complexity entropy encoder like Golomb–Rice code as the entropy coding for the proposed method.

C. CONTENT-ADAPTIVE GOLOMB-RICE CODE

In 1960, W. Golomb developed a data compression scheme called Golomb coding, which depends on entropy encoding and geometric distribution. Geometric distribution is quite suitable for modeling prediction error with higher probability of smaller prediction error compared to other methods. In particular, a Rice code corresponds to a Golomb code in which the tunable parameter is a power of two. This makes Golomb-Rice code convenient for use on a computer since multiplication and division by 2 can be implemented using a bit-shift operation; it can be performed extremely quickly. Moreover, in ECG data occurrence of small values is pretty high as compared to large values so Golomb code will be quite useful as it has optimal prefix code. The Golomb-Rice

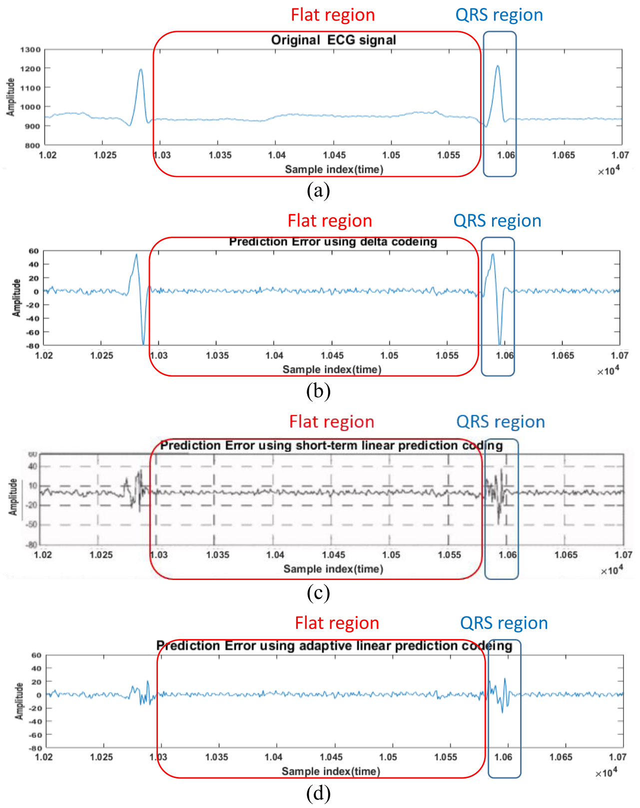

FIGURE 9. Prediction error with MIT/BIH Lead II # 100. (a) Original ECG signal, (b) prediction error with delta coding [21], (c) prediction error with short term linear predictor [22], and (d) prediction error of proposed method.

code consists of two parts: quotient and remainder. The function is as shown in (10):

$$\begin{cases} quotient : \left\lfloor \frac{M[n]}{2^k} \right\rfloor; & encoded\ with\ unary\ code \\ remainder : M\,[n]\,mod 2^k; & encoded\ with\ binary\ code \end{cases} \tag{10}$$

where k represents a positive integer as well as the number of bits for the remainder, and $M[n]$ is the non-negative integer. A simple step generates Golomb-Rice codes as follows.

To encode a non-negative integer $M[n]$, divide $M[n]$ by 2^k. This division results in quotient $q = \lfloor M[n]/2^k \rfloor$ and remainder $r = (M[n] mod 2^k)$ such that $M[n] = q * 2^k + r$. The unary and binary codes are encoded with the quotient and the remainder to differentiate the unary code and binary code in decoding; an isolation bit, 1 bit of '0', is inserted between both. However, since the prediction error may be a negative value, it is necessary to translate the negative value to positive; the function is shown in (11), where n is the prediction error value. An alternative approach encodes the magnitude of the input using a Golomb-Rice code and uses an additional bit to encode the sign bit. Although simpler, the sign-plus magnitude approach results in lower compression ratios. A Golomb-Rice encoding table with a k parameter equal to 2 is shown as an example in Table 1.

TABLE 1. Golomb-Rice encoding table with k=2.

Prediction error, n	M[n]	quotient	remainder	Bitstream
0	0	0	0	0 00
-1	1	0	1	0 01
1	2	0	2	0 10
-2	3	0	3	0 11
2	4	1	0	1 0 00
-3	5	1	1	1 0 01
3	6	1	2	1 0 10
-4	7	1	3	1 0 11
4	8	2	0	11 0 00
-5	9	2	1	11 0 01
5	10	2	2	11 0 10
-6	11	2	3	11 0 11
6	12	3	0	111 0 00
-7	13	3	1	111 0 01
7	14	3	2	111 0 10
-8	15	3	3	111 0 11
8	16	4	0	1111 0 00

$$M\,[n] = \begin{cases} 2n, & n \geq 0 \\ 2\,|n| - 1, & n < 0 \end{cases} \tag{11}$$

In Golomb-Rice code, the coding efficiency is quite sensitive to the k parameter. This study further establishes the content-adaptive Golomb-Rice code to adaptively select the k parameter. A window is used to calculate the distribution of prediction errors. Basically, for each window, its distribution of prediction error is applied to determine the k parameter. The size of the window is determined by the QRS segment of the ECG signal. The pseudo-code flow of the k parameter estimation is shown in Table 2.

TABLE 2. Seudo- code of adaptive k-parameter estimation algorithm.

```
1). Initialize k, n to 0;
2). Set pre_count to 0;
3). Set sum_abs_error to 0;
4). Set the window size (WS) to the QRS segment of ECG signal;
5). If (pre_count < WS)
    {sum_abs_error = sum_abs_error + abs (pre_error[n]);
        n ++;
        pre_count ++ ;}
6). Set k = log2 (sum_abs_error /WS);
7). Goto 2 to 6 until all samples are processed.
```

First, the proper window size is selected according to the QRS segment of the ECG signal, and the sum of the absolute value is then calculated for the prediction error within the window. By the prediction error complexity, the k parameter can be identified in each window, as shown in Fig 10. This method is able not only to optimize the k parameter to the proper value in each window, but it can also reduce the storage of the k value for each sample. With the k parameter, the unary and binary code are set with the prediction error.

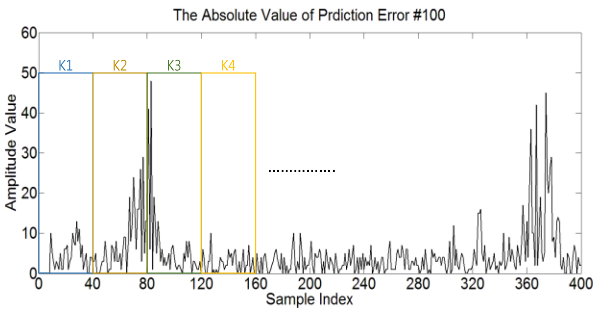

FIGURE 10. k-parameter estimation with window size.

D. DATA PACKING FORMAT

In order to compress an ECG signal in real-time, the raw signal is first separated into several segments, the size of which are determined by the window size. Second, each segment runs the proposed lossless algorithms in order. Each segment must comprise all the basic information for the decoder to reform the original signal. The bitstream of the first window must contain the first sample of ECG data with 11 bits and the k parameter with 3 bits, along with the prediction error which will be encoded by Golomb-Rice code. Since the bitstream of the first window contains the first sample, the bitstream of other windows only needs to record the k parameter and the prediction error with several bits. The output bitstream is illustrated in Fig. 11, with an example window size of 40.

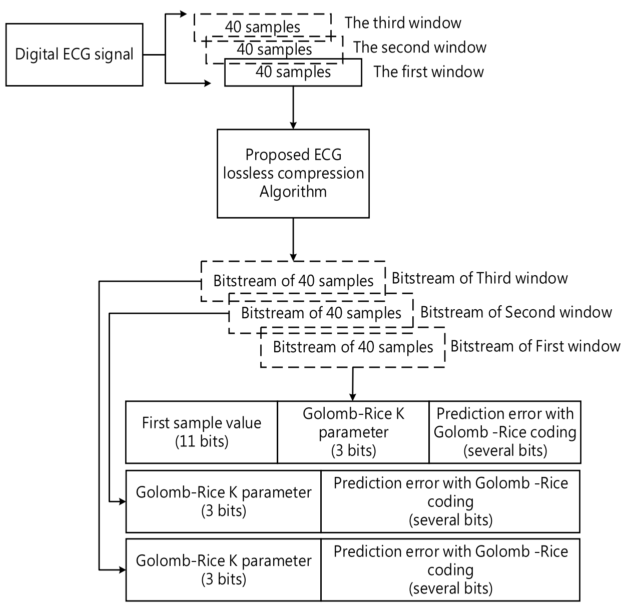

FIGURE 11. Encode bit stream format with WS=40.

III. OVERALL SYSTEM IMPLEMENTATION

The system is also developed on the ARM Cortex M4-based 32-bit MCU, which is accountable for performing ECG compression schemes and supervising various subsystems. The ECG signal is collected by three electrodes; the analog front-end amplifies the signals and converts them to digital signals so that they can undergo compression processing by the ARM M4. The pre-processed signals are then transmitted by Bluetooth. A laptop can decode the compression bitstream and immediately record the signal.

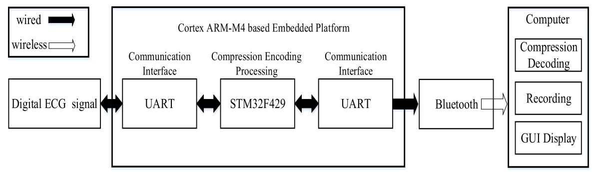

FIGURE 12. Wearable ECG monitoring system.

A. EMBEDDED SYSTEM PLATFORM

The whole wearable monitoring system constructed for the experiment in this study is illustrated in Fig. 12. The embedded platform core is STM32f429I with an ARM M4-based 32-bit MCU from ST Microelectronics, which is responsible for performing ECG compression schemes and monitoring other subsystems. The platform consists of two main subsystems: the ECG signal is obtained from the measuring device, and the Bluetooth module is used for wireless data communication. All subsystems interconnect with the MCU through separable UART peripherals, as shown in Fig. 13. The MCU is connected to a battery power supply, and dual buttons are also close to the MCU to activate/deactivate the ECG measuring device. Information related to the compressed data will also be displayed on an LCD panel, such as the amount of data processed, compression rate etc.

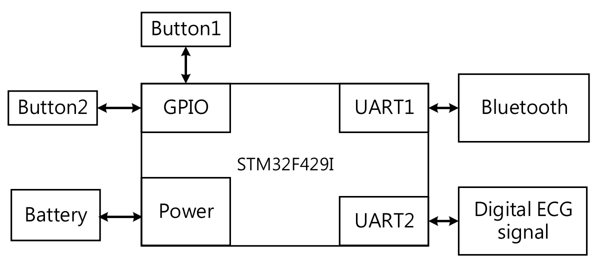

FIGURE 13. ECG platform system design.

B. ECG MEASURING DEVICE

The measuring device performed capture at a rate of 600 Hz on all twelve leads, and used a bandwidth of 0.4Hz to 160 Hz. With the RS232 protocol communication, the device provides a digital ECG signal to the development board, and the participants can observe the entire recordings in a seated position.

C. BLUETOOTH MODULE

A Bluetooth wireless module is used in the proposed system. The UART block packs the compression bitstream into the UART format. Therefore, a Bluetooth antenna can be used to transmit data to the PC wirelessly for recording and displaying the ECG signals on the screen. The Bluetooth UART module called HL-MD08R-C2A is utilized. It supports Bluetooth Serial Port Profile (SPP), baud rate 1.2k to 921.6k bps, and UART interface. This study uses these features of Bluetooth to implement the connection of the ARM M4-based embedded platform and the PC. Here, the baud rate of the UART interface between MCU and Bluetooth is set to 230400.

D. MONITOR DISPLAY MODULE

With the Bluetooth module, a PC can be used with related self-developed software to decode the compression bitstream and display the ECG signal in real time. It is also possible to set the leads of the ECG signal to display on the PC. This is very convenient for user analysis of the data.

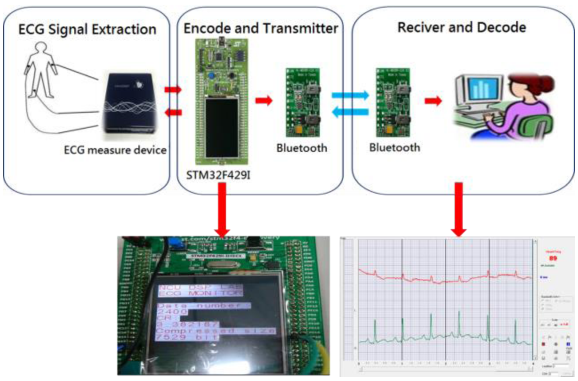

FIGURE 14. The whole demonstration system.

The whole demonstration system is constructed and shown in Fig. 14. Power is provided through USB cable to the system, so the supplied voltage is 5V, the current consumption is 25mA and power consumption is 244uA/MHz. We can extract the ECG signal on user, and then encode it in real-time manner. Several uses are tested and evaluated. The computation cycle is 2,811,351 for 30 minutes data re cording, the operation frequency is 180 MHz. The code size of ARM processor is very compact. Only about 20K Byte is used.

IV. PERFORMANCE EVALUATION AND COMPRESSION

The fraction of the compressed signal size of the original signal size is called the compression ratio (CR). It delivers all the information and ignores the unnecessary data. By reducing the CR ratio, the data bits required for storing or transmitting are obviously reduced:

$$CR = \frac{S_o}{Sc} \tag{12}$$

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

First we evaluate the result and CR for the proposed design in embedded system. As shown in Table 3, five uses are real-tested data with 10 minutes recording. The average CR for the embedded system design is 3.349.

TABLE 3. Performance of the proposed algorithm using Real-tested data.

	User1	User2	User3	User4	User5	Average
Signal Size(Byte)	360000	360000	360000	360000	360000	360000
Bitstream Size(Byte)	103270	103527	112428	117417	100784	107485
CR	3.486	3.474	3.202	3.066	3.572	3.349

TABLE 4. (Lead V1) Performance of the proposed algorithm using MIT-BIH database.

Record	CR	Record	CR
100	2.972	201	3.099
101	3.202	202	2.843
102	2.879	203	2.494
103	2.826	205	3.261
104	2.736	207	2.805
105	2.86	208	2.727
106	2.697	209	2.716
107	2.556	210	2.926
108	2.637	212	2.504
109	2.941	213	2.587
111	2.806	214	2.613
112	3.181	215	2.662
113	2.939	217	2.947
114	2.752	219	2.968
115	3.252	220	3.138
116	2.786	221	2.765
117	2.809	222	2.788
118	2.507	223	3.09
119	2.823	228	2.605
121	2.968	230	2.917
122	2.029	231	3.243
123	2.847	232	2.957
124	3.058	233	2.698
200	2.893	234	2.776
Avg. CR : 2.835 Max. CR : 3.261			

To evaluate and compare with other reference works, we need to simulate the result with benchmark. All simulations were developed in Matlab 9.2.0, and the MIT/BIH (MB) arrhythmia database was used to analyze the processing performance of the compression algorithm. With two ambulatory channels, the MB 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. In this work, the algorithm performances were evaluated by lead V1 and lead V2 ECG data. Tables 4 and 5 show the compression quality of the reported method using the MB arrhythmia database, shown below. In the Lead V1 database, the proposed method achieved an average CR of 2.835, and a maximum CR of 3.261. In the Lead V2 database, the proposed approach achieved an average CR of 2.772, and a maximum CR of 3.218. Fig. 15 shows ECG data after compression and decompression. It can be seen that both waves are identical and there is no recovery error.

Table 6 compares the performance of the proposed compression method with those of other reported techniques, and the ECG data are all taken from the MB Lead V1 database. In [19], a basic DPCM predictor and a Golomb-Rice code

TABLE 5. (Lead V2) Performance of the proposed algorithm using MIT-BIH database.

Record	CR	Record	CR
100	2.967	201	3.211
101	2.891	202	2.775
102	2.879	203	2.415
103	2.832	205	3.218
104	2.736	207	2.799
105	2.71	208	2.557
106	2.563	209	2.544
107	2.485	210	2.858
108	2.668	212	2.418
109	2.76	213	2.553
111	2.737	214	2.63
112	2.76	215	2.478
113	2.613	217	2.54
114	2.676	219	2.941
115	2.98	220	2.892
116	2.604	221	2.737
117	2.899	222	2.752
118	2.517	223	2.969
119	2.718	228	2.658
121	3.218	230	2.904
122	2.686	231	3.012
123	2.86	232	3.059
124	3.095	233	2.714
200	2.619	234	2.938
Avg. CR : 2.772 Max. CR : 3.218			

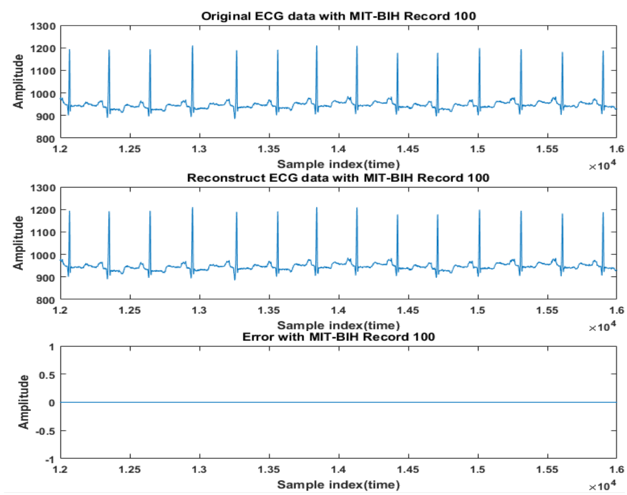

FIGURE 15. Reconstruct ECG data with MIT-BIH Record 100.

achieved a CR of 2.38; however, the DPCM predictor cannot reduce the prediction error effectively. In [22], a short term linear predictor and a fixed length packing scheme achieved a CR of 2.38. In [25], an adaptive LMS predictor and fixed length packing scheme resulted in a 2.28 CR. Although [22] and [25] provided a fixed length packing scheme with lower complexity, it is necessary to memorize the header type of the data packing to recover the original signal. In [28], a simple predictor and Huffman coding were used to obtain a CR value of 1.92. In [29], an adaptive region prediction and Modified variable length coding were applied to achieve a CR of 2.67. In [23], the adaptive linear prediction with a dual slope technique and two-stage Huffman coding produced a CR of 2.53. Although [23], [30] can offer great compression performance, Huffman code requires sufficient memory to save the code book. There are also some techniques that can offer good lossless compression performance [31], [32], but these approaches are too complex, and are thus not suitable for wearable applications. The proposed algorithm can greatly improve the average CR by about 16% over [21], [22], about 25% over [25], about 9% over [23], about 4% over [29], about 24% over [30] and about 44% over [28].

TABLE 6. Compression performance comparison with other algorithms.

Prediction technique	Entropy coding	CR	Ref
Delta predictor	Golomb-Rice coding	2.38	[21]
Short term linear predictor	Fixed length coding	2.38	[22]
LMS predictor	Fixed length coding	2.28	[25]
Adaptive linear prediction	Two-stage Huffman coding	2.53	[23]
Simple predictor	Huffman coding	1.92	[28]
Adaptive region prediction	Modified variable length coding	2.67	[29]
Fan algorithm	Huffman coding	2.10	[30]
Adaptive linear prediction	Content-adaptive Golomb-Rice coding	2.77	Proposed

V. CONCLUSION

This paper proposes a reduced complexity lossless ECG compression algorithm using an adaptive linear predictor and context-adaptive Golomb-Rice code. An adaptive linear predictor was designed to select better values and then decrease the prediction error. An improved context-adaptive Golomb-Rice code with a window size was used to optimize and reduce the storage of the k value. The proposed compression algorithm can achieve a mean compression ratio of 2.84x on the MIT/BIH arrhythmia Lead V1 database and 2.77x on the MIT/BIH arrhythmia Lead V2 database. The proposed compression method exhibits reduced complexity with high compression performance as compared to other reported methods. These results make it applicable for wearable ambulatory ECG monitoring devices. Furthermore, an ARM M4-based MCU was used to build a programmable embedded platform for signal processing, and it was applied to a wearable ECG monitoring system.

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