A Low Complexity Lossless Compression Scheme for Wearable ECG Sensors

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Abstract— This paper presents a low complexity lossless ECG compression algorithm for data reduction in wireless ambulatory ECG sensors. The proposed algorithm uses a novel linear prediction technique for redundancy removal and a joint coding-packaging scheme for compaction of the residual prediction error. Multiple linear predictors are engaged simultaneously to track the incoming data and the best prediction estimate is adaptively chosen based on the temporal signal characteristics to minimize error. An improved dynamic coding-packaging scheme frames the resulting estimation error into fixed-length 16-bit format. The proposed technique achieves an average compression ratio of 2.38x on MIT/BIH ECG database. Low complexity and good compression performance makes the proposed technique suitable for wearable ambulatory ECG monitoring applications.

I. Introduction

Cardiovascular disease (CVD) is the leading cause of death worldwide and causes roughly 31% of all global deaths[1]. The management of CVDs requires significant healthcare resources and this issue is aggravated by a fast aging population and increasing life expectancies in many countries. An effective way to address this problem is to use low cost wearable ECG sensors to monitor the patients and take proactive measures. A wearable sensor, as shown in Fig. 1, can be used to acquire, process and wirelessly transmit ECG signal to a gateway device for monitoring. The main challenge involved in the development of the sensor is to make the device low profile, unobtrusive, easy to use with long battery life for continuous usage. A high level of integration with inbuilt signal acquisition and data conversion can minimize the size, cost and power consumption of such a sensor [2], [3]. The main source of power consumption in a wearable sensor is the wireless transceiver or local flash memory in case of using burst-mode transmission[4]. The wireless transmission of data incurs high power and the use of a flash memory increases the device cost as well as power [5].

ECG data compression before transmission/storage can help to address the above issues to some extent. Although lossy compression techniques provide better compression performance, lossless compression schemes are preferred in dealing with biomedical signals, which prevent the possibility of losing any information of potential diagnostic value. Also, it is worth noting that lossy compression techniques have not been approved by medical regulatory bodies in most countries and hence cannot be used in commercial medical-grade devices. The traditional focus for lossless ECG compression was to achieve higher compression ratios. However in the context of wireless sensors and ambulatory devices, the algorithms should be low in complexity and easy in implementation. The

This work was supported in part by the National Research Foundation Competitive Research Programme under Grant NRF-CRP8-2011-01.

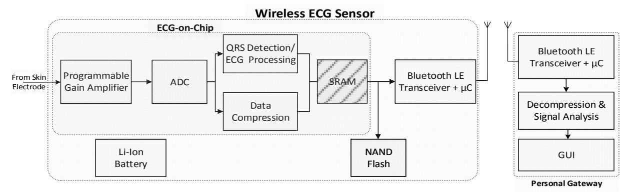

Fig.1 Wireless ECG Monitoring System

energy and memory savings obtained from the compression should be higher than what is consumed by the compressor itself.

Previously we have presented several low complexity lossless ECG compression techniques to be used in wearable sensors [6], [7]. In [6], a simple second order differential predictor is used for compression and a joint coding packaging scheme is introduced to generate a fixed length package for wireless transmission. An adaptive LMS predictor is proposed in [7] to improve the compression performance and facilitate QRS detection. Sometimes, preliminary signal processing functions like QRS detection are also implemented at the sensor to reduce overall system power[8]–[11]. In this paper, a low complexity lossless compressor to be used in wearable sensors is proposed. The main novelties are 1) a discrete-adaptive predictor which tracks the incoming signal characteristics and selects the optimal predictor from a group of 4 differential predictors is developed. The complexity of simple differential predictors are low compared to a fully adaptive predictor [7] and this results in lower overall hardware complexity while achieving good performance 2) a fixed length joint coding-packaging scheme which always frames the prediction errors into a fixed 16-bit format is used. This removes the need for further data packaging to interface in standard interfaces. This scheme was first introduced in [6] and in this work we improved it by adding frame types that consider signal characteristics. The paper is organized as follows. In Section II, III, the proposed technique is presented and its performance is evaluated. Conclusions are drawn in Section IV.

II. Lossless ECG Compression

The block diagram of a typical lossless ECG compression scheme is shown in Fig. 2. A linear predictor is used to estimate the current sample of the ECG signal, $x(n)$, from its past m samples, i.e.

$$\hat{x}(n) = \sum_{k=1}^{m} h^k x(n-k), \quad (1)$$

where $\hat{x}(n)$ is the estimate of $x(n)$ and h^k is the predictor coefficient.

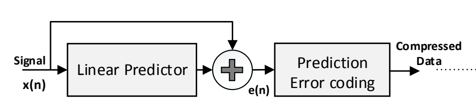

Fig.2 Typical Lossless ECG Compression Scheme

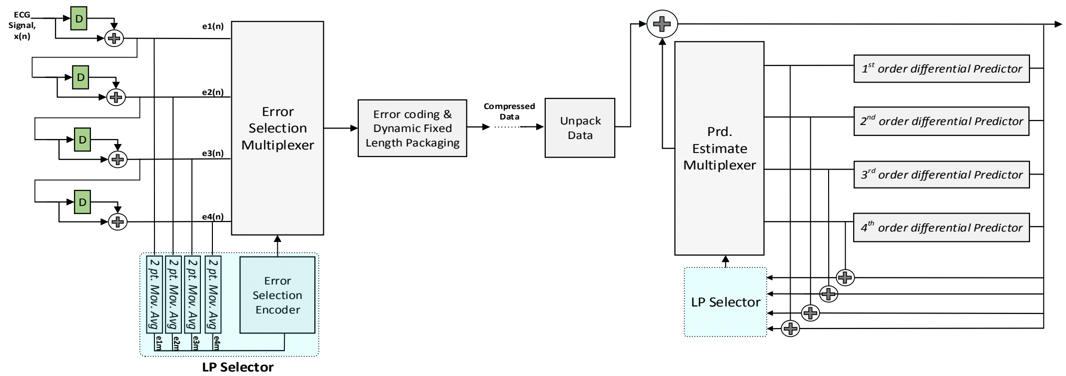

Fig.3 Lossless compression-decompression scheme.

Further, the estimated value is subtracted from the actual value of the sample to reduce the redundancy between these samples and obtain the prediction error, $e(n)$, before further coding and storage/transmission.

$$e(n) = x(n) - \hat{x}(n) \tag{2}$$

In [6], it was identified that simple differential predictors with integer coefficients have lower implementation complexity and are good choices for estimating ECG. Several low-order (1st to 4th) differential predictors were proposed in (3) to (6).

$$\hat{x}(n) = x(n-1) \tag{3}$$

$$\hat{x}(n) = 2 * x(n-1) - x(n-2) \tag{4}$$

$$\hat{x}(n) = 3 * x(n-1) - 3 * x(n-2) + x(n-3) \tag{5}$$

$$\hat{x}(n) = 4 * x(n-1) - 6 * x(n-2) + 4 * x(n-3) - x(n-4) \tag{6}$$

The error from each predictor can be calculated by simply computing the differential of the previous order prediction error as given in (7-10), where $e1(n)$, $e2(n)$, $e3(n)$, $e4(n)$ are the prediction from the 1st to 4th-order predictors, respectively.

$$e1(n) = x(n) - x(n-1) \tag{7}$$

$$e2(n) = e1(n) - e1(n-1) \tag{8}$$

$$e3(n) = e2(n) - e2(n-1) \tag{9}$$

$$e4(n) = e3(n) - e3(n-1) \tag{10}$$

Due to time based variation of the ECG signal statistics, the above predictors perform differently for various segments of the ECG signal. In [6], a 2nd-order differential predictor was chosen for redundancy reduction as it had the lower overall prediction error. In [7], an adaptive LMS based approach was used for prediction in a joint QRS detection and data compression scheme. This approach is capable of closely tracking the changes in signal characteristics. However the requirements for higher compression performance (i.e lower prediction error) was conflicting with the requirements of improved QRS detection [7]. Therefore, the algorithm was designed to achieve a balanced performance.

III. PROPOSED LOSSLESS COMPRESSION SCHEME

To improve the compression performance, prediction error should be as low as possible. To minimize the prediction error, we propose to use 4 simple differential predictors simultaneously and adaptively selecting the predictor that is optimal based on the temporal signal characteristics. It was noted in [6] that, for segments with large amplitude variation (for example the QRS segment), higher order predictors performs better and for slow varying segments lower order predictors performs better. So selecting the predictors based on temporal signal characteristics can improve the overall prediction performance similar to that of using an adaptive LMS predictor. In addition, simple differential predictors doesn't need multipliers for implementation, and therefore implementation complexity will be low compared to the adaptive LMS approach [7]. The block diagram of the proposed schemes is given in Fig. 3.

A) ADAPTIVE PREDICTOR SELECTION.

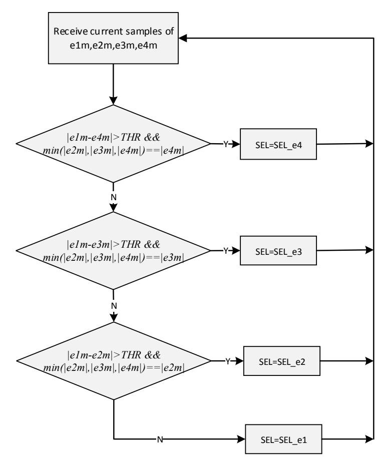

Fig.4 Predictor Selection Encoder flowchart.

In order to minimize the overall error, the predictor with best estimate has to be chosen. A simple way to do this is to compare the prediction error from all the predictors and chose the one that has the lowest error. However, the disadvantage of this approach is that, we need to explicitly identify which predictor has been used for the current sample and this may cause additional overhead of 2 bits per sample. In order to minimize this overhead, we have developed a simple approach, which will select the predictor for the next sample, based on its prediction performance for the past 2 samples. This way, no overhead bits are required to identify the predictor used during de-compression. A moving average filter is used to obtain the average error for the past 2 samples. i e. $e1m$, $e2m$, $e3m$, $e4m$. If the magnitude of difference of average prediction errors of any predictor compared to the 1st order predictor is above a threshold, *THR*, then the estimate from that predictor is used for the next sample, provided it has lowest error among all the other predictors. The detailed flow chart for the predictor selection encoder is shown in Fig. 4.

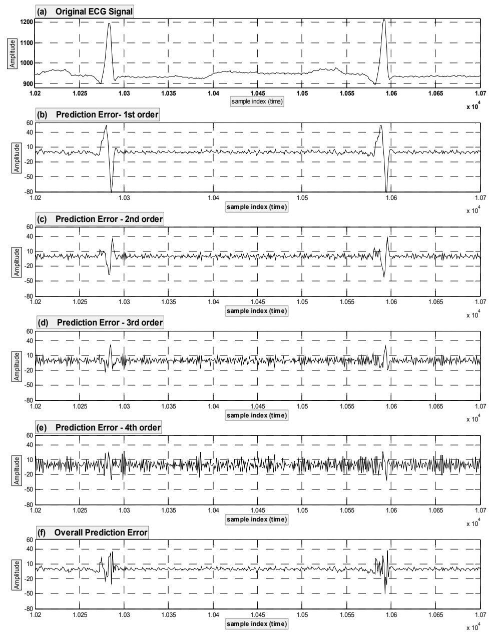

Fig.5 Prediction Error from diff predictors with MIT/BIH tape 100.

The prediction performance of all the four predictors and the combined error is illustrated in Fig. 5. Fig. 5a is the original ECG signal. Figs. 5b-5e are the prediction errors from differential predictors with varying order of 1 to 4. Fig. 5f is the adaptively combined error, which is the lowest for all segments of the ECG signal. To quantify the prediction performance and find the best overall predictor, mean absolute prediction error (MAPE) and mean-square prediction error (MSPE) for 4 predictors are computed as given in (11-12).

$$MAPE = \frac{1}{N}\sum_{n=1}^{N}|x(n) - \hat{x}(n)| \qquad (11)$$

$$MSPE = \frac{1}{N}\sum_{n=1}^{N}|x(n) - \hat{x}(n)|^2 \qquad (12)$$

The MAPE and MSPE for all the predictors were computed using MIT/BIH database. It can be found from Table I that the adaptively combined predictor yielded the lowest prediction error.

TABLE I
Mean & Mean Square Prediction Error for Selected MIT/BIH Tapes

	MIT/BIH Tape 102		MIT/BIH Tape 201	
	MAPE	MSPE	MAPE	MSPE
1st order predictor	5.09	222.16	4.16	72.14
2nd order Predictor	3.55	48.79	3.21	21.97
3rd Order predictor	4.49	48.4	4.66	45.08
4th Order Predictor	7.50	126.2	8.17	140.75
Proposed Predictor	3.15	39.22	2.91	21.26

B) Data Coding-Packaging

The dynamic range of prediction error is much smaller than that of the ECG signal as shown in Fig. 5f. Further, a coding scheme is used to reduce the bit-width of prediction error without incurring any data loss. Instead of transmitting the whole sample, only the coded data has to be stored/transmitted, resulting in power/memory savings. For coding the error, *variable length coding* schemes like Huffman and Arithmetic coding[12] can be used. However due to the implementation complexity/performance of the these coding schemes when used in a low cost sensor, a joint coding packaging scheme was proposed in [6]. The joint coding packaging scheme dynamically frames the remaining prediction error, coded in 2's complement format, into a practical, fixed length 16-bit output and has low implementation complexity. Each individual data packet is marked with a unique header so as to easily identify and decode the data while decompressing. The data packaging format is listed in Table II.

In comparison with [6], we improved the packaging scheme by adding a new packaging frame, Type F (Table II) which packs 5 prediction error samples at once. Type F frame can consist of up to two 3 bit samples at the edges and three 2 bit samples towards the middle. This specific bit arrangement can cater for a rising edge or a falling edge in the prediction error stream and thus exploits the characteristics of error signal to improve the compression performance.

The dynamic data packaging scheme uses a simple priority encoding technique to frame data from samples of multiple bit widths similar to [6]. The algorithm attempts to frame the most data into one frame (from Table II) by checking its amplitudes and opts for the next best framing option if unsuccessful as shown Fig.6.

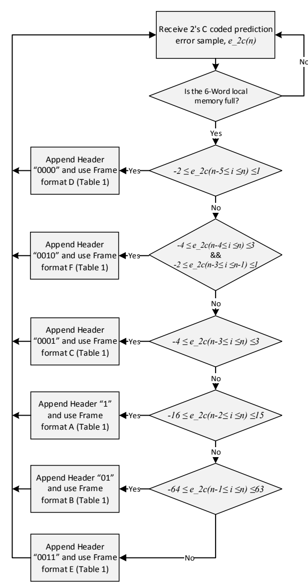

Fig 6. Coding-packaging Scheme Flowchart.

TABLE II
Data Packaging scheme for 2's Coded prediction error symbols.

<table>
<tr><td>A</td><td>1</td><td colspan="5">5/4 bits</td><td colspan="5">5/4 bits</td><td colspan="5">5/4 bits</td></tr>
<tr><td>B</td><td>0</td><td>1</td><td colspan="7">7/6 bits</td><td colspan="7">7/6 bits</td></tr>
<tr><td>C</td><td>0</td><td>0</td><td>0</td><td>1</td><td colspan="3">3 bits</td><td colspan="3">3 bits</td><td colspan="3">3 bits</td><td colspan="3">3 bits</td></tr>
<tr><td>D</td><td>0</td><td>0</td><td>0</td><td>0</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td></tr>
<tr><td>E</td><td>0</td><td>0</td><td>1</td><td>1</td><td colspan="12">12 bits</td></tr>
<tr><td>F</td><td>0</td><td>0</td><td>1</td><td>0</td><td colspan="3">3 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="2">2 bits</td><td colspan="3">3 bits</td></tr>
</table>

16 bits

Frame Type	**Header**	**Data**

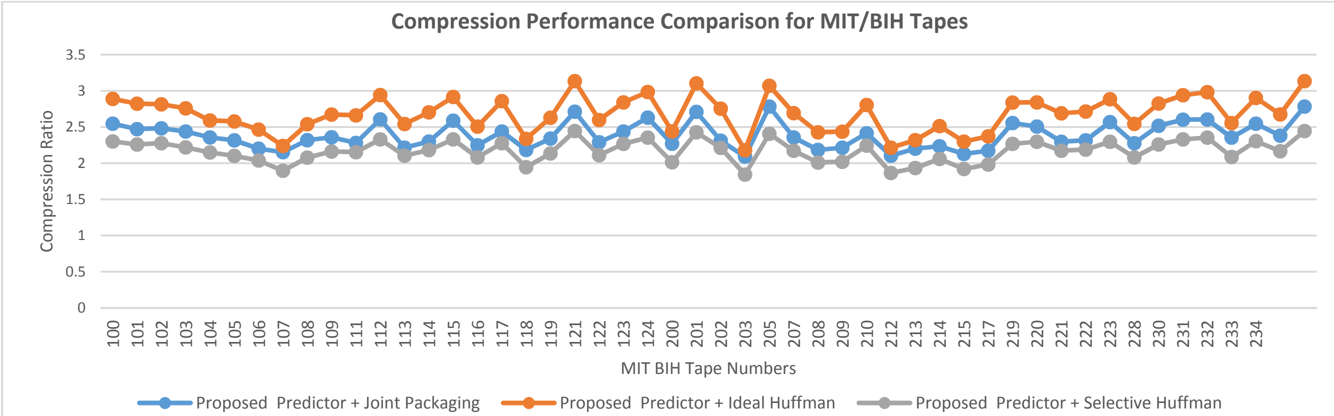

Fig. 7. Comparison of prediction error for 48 MIT/BIH records.

C) Data compression performance.

The proposed data compression algorithm is tested using the MIT/BIH Arrhythmia Database for analyzing the compression performance. The bit compression ratio (CR) is computed as in [7]. The compression performance is compared with Statistical, Selective Huffman coding using the same predictor and is given in Table III. Comparison of individual data records is shown in Fig 7.

TABLE III
Compression Performance of the proposed algorithm using the MIT/BIH database

	Proposed Predictor +Ideal Huffman	Proposed Predictor +Selective Huffman	Proposed Predictor + Joint packaging Scheme
Average CR	2.67	2.17	2.38
Maximum CR	3.13	2.44	2.78

TABLE IV
Compression Performance Comparison with Other algorithms

Method	CR	Ref
Delta Predictor/Rice Golomb Coding	2.38	[12]
Simple Predictor/ Huffman Coding	1.92	[13]
Slope Predictor/ Fix. length Packaging	2.25	[6]
Adaptive LMS/Fix. Length Packaging	2.28	[7]
Proposed Scheme	2.38	-

Table IV compares the compression performance of the proposed approach with other techniques implemented for wearable applications. In [12], a delta predictor and a context-based Rice-Golomb Coding scheme are utilized to achieve a CR of 2.38. However, the context-based Rice-Golomb coding has higher complexity since it requires on chip memory block for storage and retrieval of the context statistics as described in [12]. In [14], a 2-stage predictor and Huffman coding achieves a CR of 2.43. But as noted in [6] it uses 9 bit to represent uncoded prediction error and therefore is not completely lossless. Also [14] generates variable length coded data and would need further packaging to interface with a standard IO. In [13], a simple predictor and Huffman coding are employed to achieve a CR of 1.92. In [6], a slope predictor and fixed length packaging scheme are combined to produce a CR of 2.25. In [7], an adaptive LMS predictor and fixed length packaging scheme are used to obtain a CR of 2.28. In addition, there exist other approaches for achieving higher CR while using complex signal processing techniques. These approaches require usage of more complex hardware, which is not suitable for low power wearable applications [15], [16]. Therefore not included in the comparison. The proposed technique achieves a CR of 2.38 using adaptive predictor selection and improved fixed length packaging. As shown in Fig 3, 4, the hardware complexity of adaptive linear predictor of the compressor is ~ 11 simple adders, 5 comparators, 1 multiplexer and a few logic gates & data registers. The implementation complexity of fixed length packaging block is also low as demonstrated before in [6]. Also unlike [12], no on chip memory is required for the implementation of proposed technique which results in lower overall complexity. The proposed technique achieves ~4% improvement over [7] and ~6% improvement over [6].

IV. Conclusion

A low complexity lossless ECG compression technique suitable for wearable sensors has been presented. A novel prediction scheme which adaptively selects the best prediction estimate based on temporal signal characteristics from multiple linear predictors have been proposed to improve the performance. Also an improved dynamic coding-packaging scheme frames the resulting estimation error into fixed-length format. The proposed technique achieves an average compression ratio of 2.38x on MIT/BIH ECG database. In comparison with other published methods, the proposed algorithm has lower implementation complexity and reasonable performance and is therefore suitable for wearable wireless devices.

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