Mixed Bio-Signal Lossless Data Compressor for Portable Brain-Heart Monitoring Systems

Ericson Chua and Wai-Chi Fang, *Fellow*, IEEE

Abstract — *This paper presents a highly integrated VLSI implementation of a mixed bio-signal lossless data compressor capable of handling multichannel electroencephalogram (EEG), electrocardiogram (ECG) and diffuse optical tomography (DOT) bio-signal data for reduced storage and communication bandwidth requirements in portable, wireless brain-heart monitoring systems used in hospital or home care settings. The compressor integrated in a multiprocessor brain-heart monitoring IC comprises 15k gates and 12kbits of RAM, occupying a total area of 58k μm^2 in 65nm CMOS technology. Results demonstrate an average compression ratio (CR) of 2.05, and a simulated power consumption of 170μW at an operating condition of 24MHz clock and 1.0V core voltage. Nominal power savings of 43% and 47% at the transmitter can be achieved when employing Bluetooth and Zigbee transceivers, respectively*[1].

Index Terms — Biomedical signal processing, lossless data compression, electroencephalogram (EEG), electrocardiogram (ECG), diffuse optical tomography (DOT).

I. Introduction

Recent studies have shown that joint analysis of EEG together with heart rate variability (HRV) or brain functional near infrared spectroscopy (fNIRS) can aid in better medical diagnosis and treatment. For example, EEG and HRV data were jointly analyzed for the automatic detection of seizures in newborns [1] and sleep apnea in hospital patients [2], whereas the advantage of combined analysis of EEG and fNIRS data for cognitive rehabilitation and post-traumatic stress syndrome was presented in [3]. As a result, integrated brain-heart monitoring solutions for hospital and home care such as [4] have been proposed.

Today, portability and thus wireless transmission capability in patient monitoring systems is highly desired in order to enhance the patient's comfort and convenience. Strict restrictions on the size, weight and construction of portable devices have greatly limited their available onboard battery capacity, whereas wireless transmission of multi-channel biomedical data only aggravates the energy problem in these inherently power-isolated portable devices. Since most of the power is dissipated during wireless transmission, minimizing the amount of data through compression is essential to reduce the total system energy consumption, thereby allowing prolonged device autonomy and battery operating time.

In this paper, we propose the VLSI implementation of a mixed bio-signal lossless data compressor as a means to reduce storage and data communication bandwidth requirements prior to wireless transmission, and, as an end result, achieve lower overall power consumption in portable brain-heart monitoring systems.

The remainder of the paper is organized as follows. In Section II, we present the relationships between data compression and power consumption. In Section III, we provide a literature survey of existing lossless biomedical data compression algorithms and assess their complexity in view of hardware implementation, after which a discussion of the proposed algorithm is presented in Section IV. In Section V, we present the hardware implementation of the developed lossless compression algorithm and its integration into a DOT/EEG/ECG multiprocessor system implemented in 65nm CMOS technology. The results of the implementation are discussed in section VI, and finally a conclusion is given in Section VII.

II. Compression for Low-Power

It is well-known that wireless data communication takes up a large share of the total power consumption in most portable wireless devices or systems, with power dissipation proportional to the amount of data transferred. By compressing the data prior to wireless transmission, power can be saved provided that the compression operation itself does not consume too much power. A power tradeoff analysis for wireless EEG systems was presented in [5], showing the relationships among compression ratio (CR), power required to perform compression (P_{comp}), and power required for wireless transmission (P_{tx}). If $P_{comp} + CR^{-1} \bullet P_{tx} < P_{tx}$, then total power consumption can be reduced.

For short-range, low data bandwidth applications such as brain-heart signal monitoring, the Bluetooth and Zigbee wireless protocols are recommended over ultra-wideband and Wi-Fi [6]. Table I shows a comparison of various commercial wireless transceiver ICs in terms of their power-related characteristics assuming nominal operating usage. The lower operating current draw of the Bluetooth and Zigbee ICs is particularly attractive, especially in applications with low-power requirements such as portable biomedical devices.

[1] This work was supported in part by National Chiao Tung University and the National Science Council under the grants NSC-99-2220-E-009-028, NSC-99-2220-E-009-030, and NSC-99-220-E-009-071. The authors would like to thank to the National Chip Implementation Center and UMC University Shuttle Program for chip fabrication.

The authors are with the Department of Electrical Engineering and Institute of Electronics, National Chiao Tung University, Hsinchu 30010, Taiwan, R.O.C. (e-mail: hyptoneric.eecs97g@nctu.edu.tw; wfang@mail.nctu.edu.tw).

Manuscript received 01/15/11
Current version published 02/21/11
Electronic version published 02/21/11.

TABLE I
ENERGY CONSUMPTION OF COMMERCIAL TRANSCEIVER ICS

Protocol	Bluetooth	Zigbee	UWB	Wi-Fi
Chipset	BlueCore2	CC2430	XS110	CX53111
VDD (V)	1.8	3.0	3.3	3.3
TX (mA)	57	24.7	227.3	219
RX (mA)	47	27	227.3	215
Bit rate (Mb/s)	0.72	0.25	114	54
Energy consumption (nJ/bit)	*143*	*296*	*6.5*	*13.4*

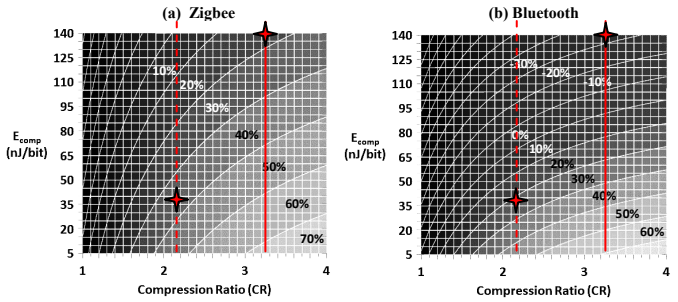


Fig. 1. Energy savings $(1 - (CR^{-1}*E_{tx} + E_{comp})/E_{tx})$ in percent as a function of E_{comp} and CR using (a) Zigbee and (b) Bluetooth transceiver ICs. Solid and dotted red lines correspond to the CRs of [8] and [9] respectively.

TABLE II
VARIOUS BIOMEDICAL DATA COMPRESSION ALGORITHMS

Reference	Biomedical Signal	Algorithm			Compression Ratio (CR)
		Prediction	Transform	Entropy Coding	
[7]	EEG (16-bit)	DPCM	Integer Karhunen–Loève Transform, Stereo Integer DCT	Huffman	2.80
[8]	EEG (16-bit)	SLP Neural Network, Adaptive Error Modeling, Context-Based Bias Cancellation	--	Arithmetic	3.23
[9]	EEG (16-bit)	Auto-Regression Filter, Context-Based Bias Cancellation	--	Conditional Coding, Huffman	2.16 (approx.)
[10]	ECG (11-bit)	Auto-Regression Filter	Burrows-Wheeler Transform, Inversion Ranks	Arithmetic	3.41 (approx.)
[11]	ECG (11-bit)	Short-Term Prediction (Context-Based Bias Cancellation), Long-Term Prediction (R-R Interval)	--	Golomb-Rice	3.49 (approx.)
[12]	ECG (13-bit)	Lempel-Ziv '77/Complex Extract	--	Exp-Golomb/Huffman	2.23/2.18

In order to save energy, a common practice is to turn on the transceiver only when data is available for transmission. Thus, when data bandwidth utilization is low, the transceiver spends most of its time in "sleep" mode, minimizing unnecessary energy consumption. Since power-up and power-down overheads are minimal, duty cycling can result in considerable energy savings. From an operational point of view, data compression can reduce the energy consumption even further by effecting a reduction in the amount of transmission data and essentially the resulting duty cycle. Fig. 1 illustrates the possible energy savings E_{saved} as a function of CR and E_{comp} for cases employing a commercial Bluetooth or Zigbee transceiver IC. Energy savings can be maximized if a good compression ratio can be realized at a minimal energy consumption cost, but may become negative when CR is too low or when E_{comp} is too high.

III. SURVEY OF BIOMEDICAL SIGNAL COMPRESSION ALGORITHMS

Many biomedical data compression algorithms have already been developed in the past, mostly for EEG and ECG signals, and can be classified as either lossy or lossless. For brain-heart monitoring systems, we only consider lossless compression techniques in order to avoid the possibility of losing biomedical signal artifacts of potential diagnostic value. Table II shows a survey of various lossless biomedical data compression algorithms and their reported compression ratio performance. Since the compression ratio is highly sensitive to the characteristics of the input data (e.g. type of biomedical signal, sample precision, sampling frequency, slew rate, etc.), and most works were done independently using their own input data sets, the reported figures above only suggest expected compression performance possible within the bounds of standard clinical practice, and should not be objectively compared against each other. In summary, published lossless compression techniques report average compression ratio figures of 2.16 to 3.23 for EEG and 2.18 to 3.49 for ECG signals.

However, unlike traditional data compression applications where storage space reduction and hence CR is the primary, and usually only, figure of merit, compression for low overall system power requires the algorithm's space-time complexity to be considered as well. For example, [8] is exceedingly superior over [9] as far as the compression ratio is concerned, but then requires large buffers and numerous computational iterations for training and accurate error modeling. In a hardware implementation point of view, the former is expected to require significantly more memory and computational elements or iterations, resulting in higher leakage and switching power consumption. As an illustration, Fig. 1 shows how an algorithm with modest compression performance can be more suitable in a particular application when power consumption is also considered. Note that the power consumption points in the figure are indicated only for discussion purposes and do not represent actual results.

A. Algorithm Complexity Considerations

In order to select a suitable candidate for a baseline hardware implementation, an assessment of algorithm complexity in the literature is presented. Most algorithms comprise a prediction step followed by entropy coding. More powerful algorithms [7], [10] additionally employ a lossless reversible transform in between, typically resulting in improved compression ratios. However, aside from introducing considerable computational overheads, transforms cause data dependencies that require sample buffering, negatively impacting power consumption as well as latency. With respect to low power compression, the inclusion of transforms is generally not recommended.

1) Entropy Coding Complexity

Entropy coding is an essential step in compression algorithms, where frequently occurring values or symbols are mapped to shorter binary sequences and less frequent ones to longer sequences. In the literature, the entropy coding step is well-represented by Huffman, arithmetic and variations of Golomb coding. Although Huffman and arithmetic codes can closely follow source entropies, they require the upkeep of large memory structures for modeling source symbol probabilities. Alternatively, Golomb coding only requires the storage and estimation of a single code scaling parameter, since it assumes a particular shape of symbol probability distribution. Because predictive coding of biomedical signals roughly satisfies the statistical assumptions of Golomb coding, the resulting entropy coding performance is only slightly inferior from optimal (by around 5%), but the hardware complexity can be significantly much lower. Hence, for entropy coding, the power of two variant of Golomb coding, Golomb-Rice, is suggested.

2) Prediction Complexity

Another important problem distinct from entropy coding is prediction. Prediction attempts to model the source signal such that an estimate of the current sample can be derived from previous samples. If the prediction can be recreated at the decoder side, then only the difference between the original and prediction values, called the prediction error, needs to be transmitted. An accurate predictor yields very small prediction errors, resulting in a low entropy signal that encodes efficiently into a shorter binary sequence after entropy coding.

Prediction techniques for biomedical signals range from the very simple like discrete pulse code modulation (DPCM) (where the previous sample is taken as the expected value for the current sample) to memory-intensive and computationally involved ones like neural networks [8], auto-regression (AR) filters [9]-[11], Lempel-Ziv and complex extraction [12].

As mentioned earlier, most works focus only on the compression ratio, and hence take full advantage of more sophisticated mathematical techniques in order to achieve better prediction. For example, AR modeling and neural networks require multiple training iterations to be run against long sequences of samples in order to find precise floating-point model parameters that yield good prediction. Similarly, the Lempel-Ziv and complex extraction methods perform pattern or template matching on blocks of samples, exploiting the periodicity of ECG signals [12]. For the same reasons, the above methods are generally considered unsuitable for real-time, low power hardware implementation.

B. Context-Based Bias Cancellation

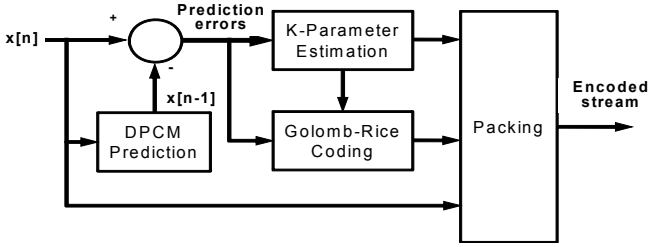
In [9], although the best reported compression ratio was associated with a 6th order AR predictor, it was shown that a very simple DPCM predictor, coupled with a computationally simple context-based bias cancellation, can attain compression performance close to that of more complicated techniques such as the AR model. In this scheme, contexts are defined based on past samples, and the typical DPCM prediction error in each context is estimated. By subtracting this estimate from the original prediction, an improved prediction can be achieved. Due to its simplicity, the method is seen to be very suitable for low power compression.

From the foregoing discussions in the previous sections, the prediction technique based on a DPCM predictor with context-based bias cancellation [9] shows most promise, while an entropy coding method based on Golomb-Rice is recommended due to its low complexity and good entropy coding performance. In the next section, we proceed to describe the chosen lossless data compression algorithm in more detail.

IV. Proposed Algorithm for Low-Power Biomedical Systems

A. Basic DPCM Prediction with Golomb-Rice Entropy Coding

The proposed lossless data compression algorithm is largely based on a basic discrete pulse code modulation (DPCM) predictor followed by Golomb-Rice entropy coding, whose block diagram and algorithm flow is shown in Fig. 2. The




```
1. Set Window Size WS = 64, 128 or 256
2. Set Sample Precision SP = 8 or 10
3. Output the first sample x[0]
4. Set sample pointer S_PTR = 1
5. Set SUM_ABS_ERR = 0
6. For n from S_PTR to S_PTR+WS-1:
   Set SUM_ABS_ERR = SUM_ABS_ERR
   + abs(x[n]-x[n-1])
7. Set K = ceil(log2(SUM_ABS_ERR/WS))
8. Output Golomb-Rice parameter K
9. For n from S_PTR to S_PTR+WS-1:
   Output GR_ENCODE(x[n]-x[n-1], K)
10. Advance to next window: S_PTR = S_PTR + WS
11. Repeat steps 5 to 10 until all samples
    are processed
```

Fig. 2. Basic DPCM prediction followed by Golomb-Rice entropy coding described as a block diagram (top) and pseudo code (bottom).

previous sample is taken as the prediction for the current sample, and the prediction error is obtained by subtracting the two. From a window size WS of prediction errors, the Golomb-Rice code scaling K parameter is estimated and the prediction errors are Golomb-Rice entropy coded using this parameter. Finally, the encoded stream is packed into data chunks of fixed width for output.

DPCM prediction is partly able to model the redundancies between consecutive samples, such that the resulting frequency distribution of prediction errors tends to center and peak near zero, as shown in Fig. 3a. From this distribution, an appropriate K parameter can be estimated, such that distributions with smaller variances result in smaller K and distributions with larger variances result in larger K. A Golomb-Rice encoding table with K parameter equal to 2 is shown as an example in Fig. 3b. Since smaller symbol (the prediction error is taken as the symbol) values occur more frequently, shorter code lengths dominate, resulting in overall compression. Finally, the encoded output stream, illustrated in Fig. 3c, contains all the necessary information for the decoder to reconstruct the original signal.

B. Context Modeling

A typical overall distribution of prediction errors after DPCM is shown in Fig. 3a, and is typically zero-mean with an overall variance to which an optimal K parameter is associated. However, it has been demonstrated in earlier literature [9], [14] that the overall Laplacian distribution is actually a composition of a plurality of Laplacian distributions, each having its own variance and mean shift away from zero (Fig. 3a). By appropriately defining a context model, these individual structures can be extracted, upon which 1) bias cancellation can be performed to re-center each distribution back to zero, resulting in smaller prediction errors; and 2) more optimal Golomb-Rice K parameters can be estimated for each distribution.

A simple yet effective context model definition based on the past five sample differences was suggested in [9] for EEG signals, and is depicted in Fig. 4. The current sample is x_k, and the sample differences d_i are defined as

$$d_i = x_{k-i} - x_{k-i-1} \tag{1}$$

where i is an integer between 1 and 5, inclusive, indexing the past five samples. To limit the number of contexts, the sample differences are quantized according to (2) with $T = 0$, resulting in a total of 32 contexts.

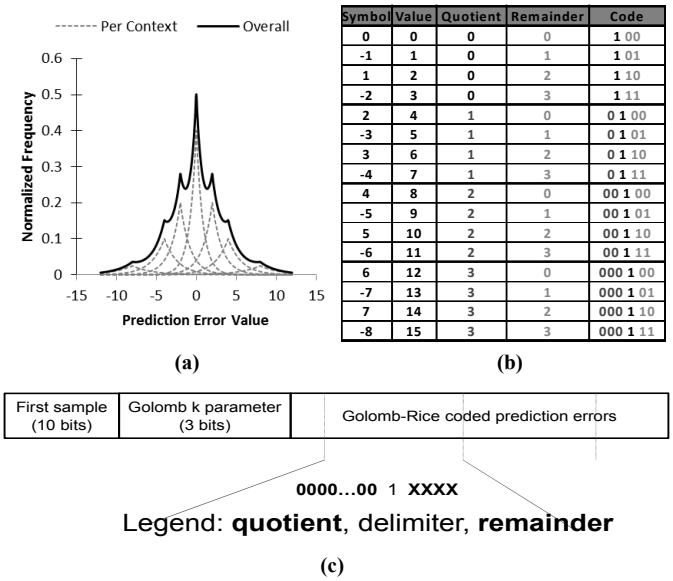
$$Q(d_i) = \begin{cases} 0, & if\ d_i < T \\ 1, & if\ d_i \geq T \end{cases} \tag{2}$$

Finally, the context is defined by (3).

$$context(x_k) = \{Q(d_1), Q(d_2), Q(d_3), Q(d_4), Q(d_5)\} \tag{3}$$

C. Bias Estimation and Cancellation

For a particular context, the bias cancellation estimate is taken as the average prediction error occurring in that context. For example, the simple DPCM prediction for a current sample in an "always increasing" context (i.e. $context(x_k) = \{1,1,1,1,1\}$ tends to be short by some positive value. This bias is added back to the DPCM prediction, and the result is a shorter binary code sequence after Golomb-Rice coding.



Symbol	Value	Quotient	Remainder	Code
0	0	0	0	1 00
-1	1	0	1	1 01
1	2	0	2	1 10
-2	3	0	3	1 11
2	4	1	0	0 1 00
-3	5	1	1	0 1 01
3	6	1	2	0 1 10
-4	7	1	3	0 1 11
4	8	2	0	00 1 00
-5	9	2	1	00 1 01
5	10	2	2	00 1 10
-6	11	2	3	00 1 11
6	12	3	0	000 1 00
-7	13	3	1	000 1 01
7	14	3	2	000 1 10
-8	15	3	3	000 1 11

Fig. 3. (a) Prediction error distribution and its mapping to (b) Golomb-Rice encoding table with K = 2; (c) Encoded output stream.

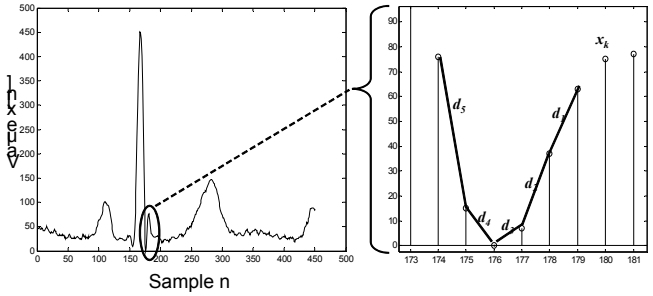


Fig. 4. Context model based on five past sample differences, where the context of x_k is a function of d_1 to d_5.

D. Latency Reduction

From a system point of view, a major disadvantage of the algorithm described thus far is its high output latency. Ideally, once a biomedical data sample (e.g. EEG, ECG) is sensed, it can be immediately shown on the display device. Since the Golomb-Rice encoder can only start outputting when the K parameter or bias cancellation value C has been calculated, the latency is seen to be the window size WS. From simulation results, the window size WS must be large enough (typically a quarter to half the period) to achieve reasonable compression performance. In many clinical situations, a latency of half a second is already unacceptable.

To solve this problem, the estimation loop for the K parameter and bias cancellation value C is opened and is instead performed on a per sample basis according to [13]. As an additional benefit of this scheme, since at any time, the estimates are based on past samples only, the estimation procedure can be performed in exactly the same manner at the decoder, and hence both the K parameter and bias cancellation value C need not be transmitted as part of the output coded stream anymore.

V. Hardware Implementation

A. Integration in a DOT/EEG/ECG Multiprocessor System for Brain-Heart Monitoring

The developed algorithm is implemented in hardware and integrated in a multiprocessor brain-heart monitoring system [4] for the real-time lossless compression of multichannel discrete optical tomography (DOT), electroencephalogram (EEG) and electrocardiogram (ECG) biomedical data. Fig. 5 shows the scope and application of the developed mixed bio-signal lossless data compressor and a summary of the system specifications relevant to the lossless data compression unit is presented in Table III.

The complete system operates as follows. A sensor control unit controls the acquisition of multichannel EEG, ECG and DOT data according to their specified sampling frequencies, after which each bio-signal is relayed to its corresponding signal processing engine. EEG data undergo independent component analysis (ICA), ECG data undergo heart rate variability analysis, and fNIRS data is processed for the reconstruction of a diffuse optical tomography image. Depending on user settings, the ICA and HRV engines can also be bypassed to support applications that only require raw EEG or ECG data acquisition. Raw or processed bio-signal data is then losslessly compressed in the proposed compressor and finally multiplexed into a single data stream and sent out of the chip in real-time through an output UART interface. Finally, the mixed multichannel data is sent off wirelessly to the base station device through a Zigbee wireless communication interface.

With each packet containing only EEG, ECG or DOT data distinguished by a data type header, homogeneous encoded streams can be received and decoded independently on a mains-powered base station and subsequently displayed on a real-time display device. Alternatively, a bypass mode is also provided such that raw bio-signal data skips the compression operation and is transmitted as is, uncompressed.

B. Hardware Architecture

The hardware architecture of the proposed lossless data compressor unit, shown in Fig. 6, comprises four pipeline stages including first, a priority data selector (PDS) stage, second, a prediction and parameter estimation stage, third, a Golomb-Rice entropy coding stage (shaded in gray), and lastly an output packaging stage. Since Golomb-Rice codes vary in length, the number of clock cycles to completely pack an encoded stream onto a fixed bus width varies at the final packing stage. To prevent pipeline overflow, a ready-acknowledge handshaking mechanism is employed throughout the pipeline in every stage. Unfortunately, due to restrictions in chip real estate, the bias cancellation mechanism was forfeited; resulting in around 7% performance loss in CR. Context-based estimation of the Golomb-Rice K parameter was retained.

To conserve hardware resources, the prediction circuitry is shared among the different biomedical signals. The PDS stage serves as a multiplexer, serially sending each sample to the main compression unit (enclosed in dotted lines), at the same time indicating the biomedical signal type CHSEL and sample precision SP. The prediction stage in the main compression unit receives the current sample, determines its context and loads the context statistics from memory. In the next cycle, the K parameter is calculated, the prediction error remapped, and the context variables updated and written back to memory. The prediction stage maintains the individual memory locations for the context statistics of the different biomedical data channels. Note that for DOT, DPCM prediction is performed on an inter-frame basis, and context-based K parameter estimation is not performed, due to memory space limitations.

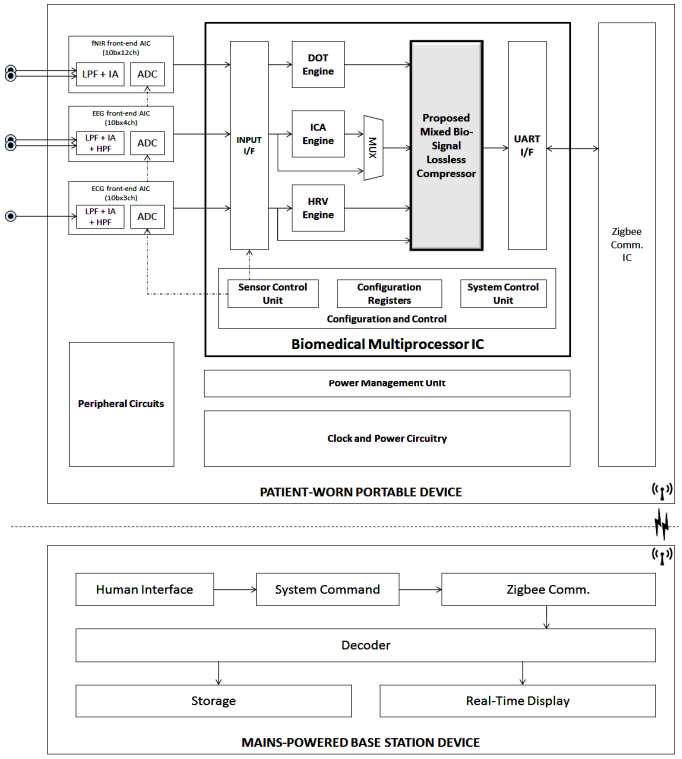


Fig. 5. Integration of proposed mixed bio-signal lossless data compressor in a brain-heart monitoring system.

TABLE III
System Specifications Related to Lossless Data Compression

Parameter	DOT	EEG	ECG
Signal Source	Change in absorption coefficients influenced by hemoglobin	Electrical activity on the scalp caused by firing neurons in the brain	Electrical changes on the skin caused by heartbeat
Sensor	fNIR LED and sensor array	EEG electrodes	ECG electrodes
Nature of Data	Video	Time-series	Time-series
Primary Function	DOT image reconstruction	Independent component analysis	Heart rate variability
Sampling Rate	1 frame/s (96 pixels)	128 Hz	256 Hz
Sample/Pixel Resolution	20-bit	10-bit	10-bit
No. of Channels	1	4	3

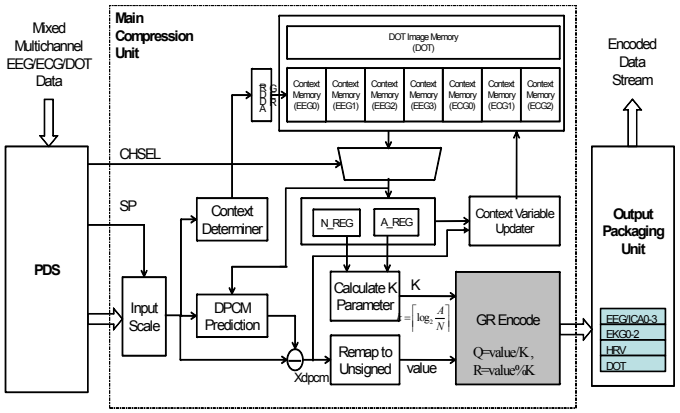


Fig. 6. Hardware architecture of proposed mixed bio-signal lossless compressor.

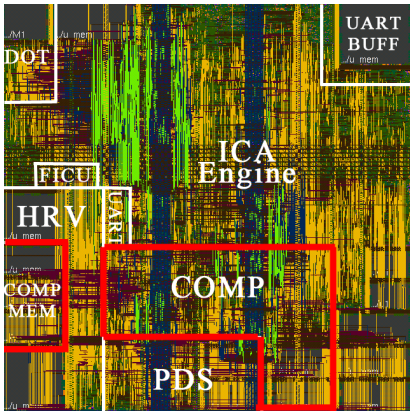


Fig. 7. Chip layout of the DOT/EEG/ECG multiprocessor implemented in 65nm CMOS, with the proposed lossless data compressor indicated.

The Golomb-Rice entropy coder, indicated in gray in Fig. 6, implements the Golomb-Rice coding table shown in Fig. 3b for various values of K. It calculates the quotient and remainder based on the estimated Golomb-Rice K parameter and input remapped prediction error, and outputs the result to the next stage within a single clock cycle.

The output packaging unit is the final pipeline stage and maintains four separate output buffers for the different biomedical signals, which are filled up as samples are encoded into bit streams. Whenever any of the buffers become full, the buffer value is driven onto the output bus, together with an appended data type ID indicating the type of biomedical data. In case two or more buffers are full simultaneously, a priority scheme is enforced such that minimal output latency is achieved.

The main compression unit, indicated by the dotted lines in Fig. 6, corresponds to the proposed algorithm described in the earlier sections to which the overhead energy consumption E_{comp} is attributed. The PDS and output packaging stages perform mainly data routing and packing, which operate regardless of whether compression is employed or not.

C. Implementation in 65nm CMOS

The DOT/EEG/ECG multiprocessor chip was implemented using 65nm CMOS technology, with the proposed compressor comprising 53,969 gates and occupying a total of 58k μm^2. Simulated power consumption using a full operation test case reports 170μW under the condition of 24MHz clock frequency and 1.0V core supply voltage. The chip layout and chip specifications are shown in Fig. 7 and Table IV respectively.

TABLE IV
DOT/EEG/ECG MULTIPROCESSOR CHIP SPECIFICATIONS

Parameter	Value	
Technology	65nm CMOS 1P10M	
Pad/Core Voltage	2.5 / 1.0 V	
System Operating Freq.	24 MHz	
Die Size	1,317 x 1,317 μm^2	
Number of PADs	104	
	Full Chip	Proposed Compressor
Core Size	462k μm^2	58k μm^2
Equivalent Gate Count	368,314	53,969
Estimated Power	3.59 mW	170 μW

TABLE V
COMPRESSION RATIO RESULTS

Bio-Signal	Compression Ratio (CR, Original/Compressed)
DOT	2.10
EEG / ICA	1.37 / 1.55
ECG	2.38
Overall (Average)	***2.05***

TABLE VI
ENERGY SAVINGS AT TRANSMITTER

	Bluetooth	Zigbee
E_{tx} (nJ/bit)	143	296
E_{total_old} (nJ/bit)	143	296
CR	2.05	
E_{tx_new} (nJ/bit)	70	144
E_{comp} (nJ/bit)	12	
E_{total_new} (nJ/bit)	82	156
Energy Savings	***43%***	***47%***

VI. RESULTS

Table V shows the average compression ratio results for the various biomedical data, as calculated from MATLAB simulations and cross-validated with post-layout simulations. For DOT, raw image pixel data were obtained from a typical laboratory demonstration setup, whereas EEG and ECG raw data were obtained from EEGLab and the MIT-BIH Arrhythmia Database, respectively. Overall, considering the number of channels, sample precision, sampling frequency and total bandwidth for each type of biomedical signal, an average CR of 2.05 was achieved. Similarly, dividing the average power consumption of the main compression unit by the total data bandwidth, the average normalized energy consumption E_{comp} of 12nJ/bit was derived. Given the normalized energy consumption E_{tx} figures of commercial Bluetooth and Zigbee ICs, the overall energy savings at the transmitter were calculated to be 43% and 47% respectively.

VII. CONCLUSION

In this paper, the VLSI implementation of a low complexity lossless biomedical data compressor was presented, demonstrating that an average lossless compression ratio of 2.05 can be achieved at a power consumption of 170μW (or normalized energy consumption of 12nJ/bit, considering data bandwidth as well) when using 65nm CMOS technology. At this given performance level and considering the compression-to-wireless transmission power trade-off relationship, 43% and 47% power savings can be achieved when employing commercial Bluetooth and Zigbee transceiver ICs, respectively.

This work represents a study to determine the power consumption figure that can be achieved by a straightforward implementation of a low-complexity lossless data compression algorithm of reasonable compression ratio performance. In the future, it will be of interest to push further the limits of low power compression in terms of E_{comp} and CR, possibly by investigating optimized implementations of more complex algorithms as well as more aggressive power optimizations at both algorithm and architectural levels.

REFERENCES

[1] Malarvili, M.B.; Mesbah, M.; , "Combining newborn EEG and HRV information for automatic seizure detection," Engineering in Medicine and Biology Society, 2008. EMBS 2008. 30th Annual International Conference of the IEEE, pp.4756-4759, 20-25 Aug. 2008.

[2] Abdullah, H.; Holland, G.; Cosic, I.; Cvetkovic, D.; , "Correlation of sleep EEG frequency bands and heart rate variability," Engineering in Medicine and Biology Society, 2009. EMBC 2009. Annual International Conference of the IEEE, pp.5014-5017, 3-6 Sept. 2009.

[3] Fidopiastis, Cali; Hughes, Charles;, "Workshop 1: Use of psychophysiological measures in virtual rehabilitation," Virtual Rehabilitation, 2008, pp.xi-xi, 25-27 Aug. 2008.

[4] Fang, Wai-Chi; Chen, Chiu-Kuo; Chua, Ericson; Fu, Chih-Chung; Tseng, Shao-Yen; Kang, Shih; , "A low power biomedical signal processing system-on-chip design for portable brain-heart monitoring systems," Green Circuits and Systems (ICGCS), 2010 International Conference on , vol., no., pp.18-23, 21-23 June 2010.

[5] Yates, D.C.; Rodriguez-Villegas, E.; , "A Key Power Trade-off in Wireless EEG Headset Design," Neural Engineering, 2007. CNE '07. 3rd International IEEE/EMBS Conference on, pp.453-456.

[6] Jin-Shyan Lee; Yu-Wei Su; Chung-Chou Shen; , "A Comparative Study of Wireless Protocols: Bluetooth, UWB, ZigBee, and Wi-Fi," Industrial Electronics Society, 2007. IECON 2007. 33rd Annual Conference of the IEEE , vol., no., pp.46-51, 5-8 Nov. 2007.

[7] Wongsawat, Y.; Oraintara, S.; Tanaka, T.; Rao, K.R.; , "Lossless multi-channel EEG compression," Circuits and Systems, 2006. ISCAS 2006. Proceedings. 2006 IEEE International Symposium on , vol., no., pp.4 pp.-1614.

[8] Sriraam, N.; Eswaran, C.; , "An Adaptive Error Modeling Scheme for the Lossless Compression of EEG Signals," Information Technology in Biomedicine, IEEE Transactions on , vol.12, no.5, pp.587-594, Sept. 2008.

[9] Memon, N.; Xuan Kong; Cinkler, J.; , "Context-based lossless and near-lossless compression of EEG signals," Information Technology in Biomedicine, IEEE Transactions on , vol.3, no.3, pp.231-238, Sept. 1999.

[10] Arnavut, Z.; , "ECG Signal Compression Based on Burrows-Wheeler Transformation and Inversion Ranks of Linear Prediction," Biomedical Engineering, IEEE Transactions on , vol.54, no.3, pp.410-418, March 2007.

[11] Giurcăneanu C.D.; Tăbuş I.; Mereuţă S.;, Using contexts and R-R interval estimation in lossless ECG compression, Computer Methods and Programs in Biomedicine, Volume 67, Issue 3, March 2002, Pages 177-186.

[12] Antti Koski, Lossless ECG encoding, Computer Methods and Programs in Biomedicine, Volume 52, Issue 1, January 1997, Pages 23-33.

[13] Weinberger, M.J.; Seroussi, G.; Sapiro, G.; , "The LOCO-I lossless image compression algorithm: principles and standardization into JPEG-LS," Image Processing, IEEE Transactions on , vol.9, no.8, pp.1309-1324, Aug 2000.

[14] Wu, X.; Memon, N.; , "Context-based, adaptive, lossless image coding," Communications, IEEE Transactions on , vol.45, no.4, pp.437-444, Apr 1997.

BIOGRAPHIES

Ericson G. Chua received his B.Sc. degree in Computer Engineering from the Department of Electrical and Electronics Engineering at the University of the Philippines, Diliman in 2002.

He is currently working towards his M.S. degree in Electronics Engineering at the National Chiao Tung University in Hsinchu, Taiwan (R.O.C.), where he is currently with the SOC Design and System Integration Laboratory at the Microelectronics and Information Systems Research Center. His major research interests include digital IC design, data compression, image processing, and video coding technologies.

Wai-Chi Fang (S'81-M'86-SM'93-F'03) received his B.S. degree from the Electronics Engineering Department at National Chiao-Tung University in 1978. He completed his M.S. degree in 1982 from the State University of New York at Stony Brook and his Ph.D. degree in 1992 at the University of Southern California.

He is currently the TSMC Chair Professor and the Director of System-on-Chip Research Center of National Chiao-Tung University. From 1985 to 2009, he had been with NASA's Jet Propulsion Laboratory (JPL), California Institute of Technology. Dr. Fang's subjects of interest include VLSI biomedical microsystems, neural networks and intelligent systems, multimedia signal processing, wireless communication, sensor networks, space integrated avionic systems, intelligent green electronic and system-on-chip design for health care applications.

He has published over a hundred papers and ten books. He is the recipient of 1995 IEEE VLSI Transactions Best Paper Award. He holds seven US patents and thirteen NASA new technologies. He is the recipient of NASA Certificates of Recognition for these creative technical innovations. He won the NASA Space Act award in 2002 and 2003. His inventions on advanced computing engines and data compression systems are used in space missions. Dr. Fang is an IEEE Fellow. He serves as an officer of IEEE Systems Council as the Vice President and the Chairman of Transnational and Liaison Committee. He also serves on the Advisory Board of IEEE Systems Journal and the Advisory Board of International Journal of Innovative Computing, Information & Control. He was an elected Governor of the IEEE Circuits and Systems Society (2004-2006 and 2007-2009) and an AdCom member of the IEEE Nanotechnology Council (2005-2006). Dr. Fang was the Chairman of IEEE CASS Technical Committee on Nanoelectronics and Gigascale Systems (2005-2007), Chairman of IEEE CASS Technical Committee on Multimedia Systems and Applications (2003-2005), and Chairman of IEEE CASS Technical Committee on Neural Systems and Applications (2001-2003). He served as Associated Editor for the IEEE Transactions on Very Large Scale Systems (1997-1998), IEEE CASS Circuit and Device Magazine (1999-2000), IEEE Transactions on Multimedia (2000-2001), and IEEE Transactions on Circuits and Systems I (2002-2003). He was the general chairman of the 2006 IEEE International Conference on Intelligent Information Hiding and Multimedia Signal Processing. He serves on Organization Committee and Technical Program Committee of many international conferences and workshops.