Lossless EEG Compression Algorithm Based on Semi-Supervised Learning for VLSI Implementation

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***Abstract*—In this paper, a hardware-oriented lossless EEG compression algorithm including a two-stage prediction, voting prediction and tri-entropy coding is proposed. In two stages prediction, 27 conditions and 6 functions are used to decide how to predict the current data from previous data. Then, voting prediction finds optimal function according to 27 conditions for best function to produce best Error (the difference of predicted data and current data). Moreover, a tri-entropy coding technique is developed based on normal distribution. The two-stage Huffman coding and Golomb-Rice coding was used to generate the binary code of Error value. In CHB-MIT Scalp EEG Database, the novel EEG compression algorithm achieves average compression rate to 2.37. The proposed hardware-oriented algorithm is suitable for VLSI implementation due to its low complexity.**

***Index Terms*—Dynamic voting, EEG, fuzzy decision, lossless, machine learning, tri-entropy coding, WBSN.**

I. Introduction

EEG (Electroencephalography, EEG) is a kind of biomedical signal, that plays an important role in neurology. This technique is built to record tiny electrical signal form human brain. It can help neurologists diagnose potential functioning disorders from brains, such as epilepsy, stroke and sleep disorders. Also, Sports Science uses EEG to monitor athlete to increase their concentration and performance. Amount all kinds of available, portable EEG device is excepted to provide comfortable and ease of accessibility during EEG signal acquisition procedure.

Recently, wireless body sensor network (WBSN) [1] has been widely used in measuring biomedical signals during these years. The WBSN provides a good solution for solving long term biomedical measurement. However, the using time per charge of wireless device is still limited by battery capacity and data transmission time. Thus, compression technique is a good way to reduce the data, which can decrease data transmission time and keep the wireless device to work more time. Previous studies [2][3] provided a brilliant compression technique to solve the limitation of wireless device. For biomedical signal, any loss of data processing is intolerable. The data missing may cause the wrong diagnosis and fail treatment. As mentioned above, a lossless EEG compression method needs to be developed for reducing data transmission time and keeping data quality.

Thus, a lossless EEG compression hardware-oriented algorithm based on semi-supervised learning technique was proposed in this study. The compression algorithm achieved 2.37 CR in CHB-MIT Scalp EEG Database and easily implemented by VLSI architecture.

II. Lossless EEG Compression Algorithm

This EEG Compression algorithm consists of two major parts, a predictor and an encoder. In the predictor part, there are three steps. First the raw data will go through first-stage prediction given this data preliminary processing. Second, the fuzzy decision is used to classify them in to different cases. Finally, the voting prediction decides an optimal outcome of the predictor part.

After receiving the outcome of the predictor, tri-entropy coding will convert the predicted value into variable length codes, as show in Fig.1. And the details of each section will be demonstrate as following.

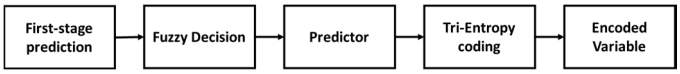


Fig.1 Lossless EEG Compression Algorithm flow

A. First-stage Prediction

There are two outcome of First-stage prediction, value diff1 and diff_2, where diff1 is defined by the difference between X(n) and X(n-1), diff2 is defined by the difference between X(n-2) and X(n-3). These two values diff1 and diff2 are also indicated the slope of the passed signals. Both of them will play an important role in the fuzzy decision section.

B. Prediction function based on machine learning

The main idea of the prediction is to create a function which uses several previous incomes X(n-1) to X(n-4) and generates an outcome PD_1. In this study a concept of supervised learning [4] was used to minimize the gap between PD_1 and X(n).

$$PD_1(n) = A_{(n)} * X(n-3) + \cdots + A_{(n+2)} * X(n-1) \quad \text{.....(1)}$$

$$Error(n) = X(n) - PD_1(n) \quad \text{.....(2)}$$

where $A_{(n)}$ is the parameter of predicted function (1). In order to find the optimal parameter $A_{(n)}$, Error(n) was define by (2) the gap between signal X(n) and PD.

With the purpose of evaluation of the performance, all the absolute values of Error(n) were sum up, and the smallest value can be seen as a batter prediction function. Because of entropy coding compression rate will be highly related to data concentration. Repeating all these steps for few times, six different functions can be obtained. Each of them offer different prediction patterns for the fluctuation of EEG signals. The six prediction functions are shown in equations (3)(4)(5)(6)(7)(8).

$$Function1\ PD = X(n-1) \quad (3)$$

$$Function2\ PD = 2*X(n-1)-X(n-2) \quad (4)$$

$$Function3\ PD = (3*X(n-1)-X(n-2))/2 \quad (5)$$

$$Function4\ PD = -X(n-2) + X(n-3) \quad (6)$$

$$Function5\ PD = 3*X(n-1)-3*X(n-2) + 3*X(n-3) \quad (7)$$

$$Function6\ PD = -3*X(n-1)-3*X(n-2) \quad (8)$$

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C. *Fuzzy Decision*

Fuzzy Decision is based on the characteristics of passing three signals and then classifying them in to several modules. According to the value of X(n-1), it can be defined in three classes, Low, Medium and High. Fig. 2 illustrates the first fuzzy decision rule. After that, the outcome of the first-stage prediction diff1 and diff2 can be classified to another three different classes, Low, Medium and High. Fig.3 illustrates the second fuzzy decision rule. According to all of the rules, the result of first-stage prediction will be sent to twenty-seven modules M1 to M27.

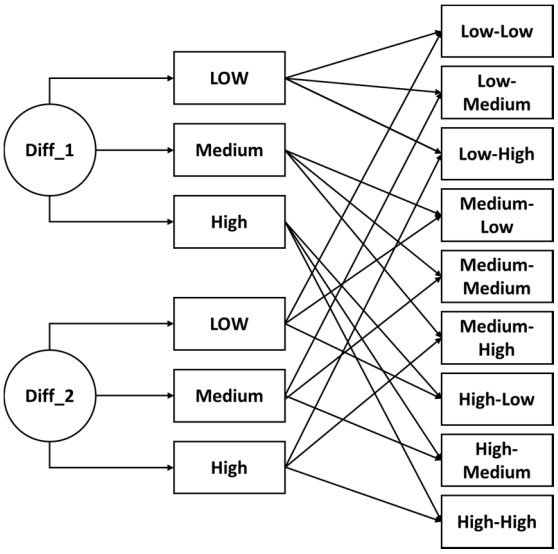


Fig.2 Block diagram of the first-stage fuzzy decision.

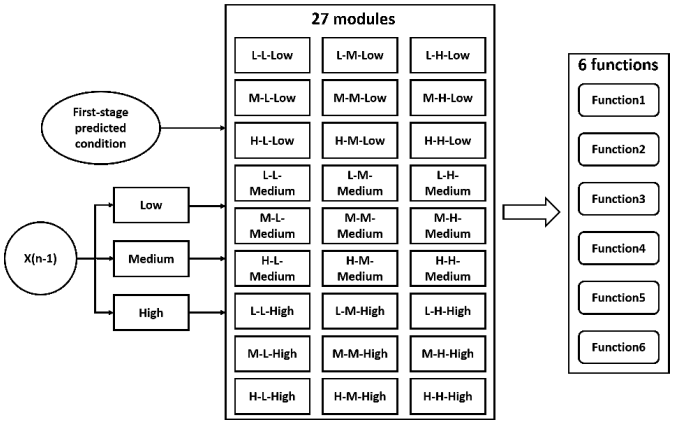


Fig.3 Block diagram of the second-stage fuzzy decision.

D. *Voting Prediction*

In order to adaptively select the best function to fit the current situation, the first-stage prediction classifies data by the passed two values of slope diff_1 and diff_2. Next, to consider the most current data X(n-1) and then put them into three different section as shown in Fig. 3. After the data denoting into twenty-seven modules from L-L-Low to H-H-High, one of six functions will be selected by the second-stage fuzzy decision module. All this work is try to provide an easy way for decoding side to recognize which prediction function was selected.

For a better understanding, Fig. 4 shows an example of the voting processing. Once data is sent to one of the twenty-seven modules, the system will check which function has most votes and selected this function as the optimal function to produce outcome PD. If they have same amount of votes, the smaller label of function has higher priority. After executing all of six prediction functions, the function which has smaller absolute value will get a vote. So in the future it can also execute this process reversely, and figure out which function is selected. In the example of Fig.4, the function_4 will be selected because it has most votes. After that, the function_2 can get a vote due to the minimum absolute value.

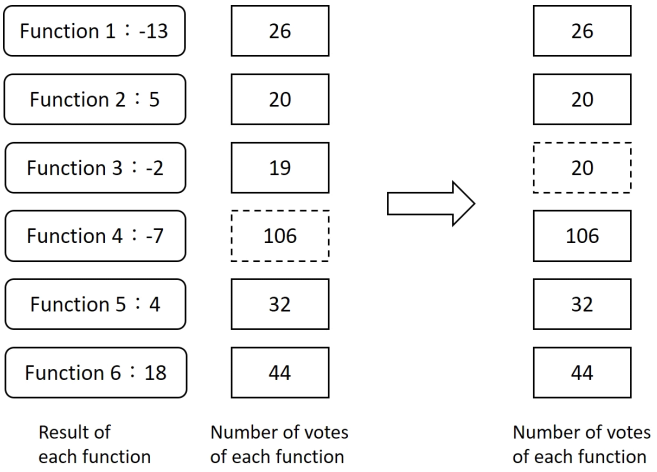


Fig.4 Example of voting prediction process.

E. *Tri-Entropy Coding*

Tri-Entropy encoder includes two layers of Huffman coding and one layer of Golomb-Rice coding algorithm. Huffman coding is based on the frequency of occurrence. Huffman coding has already been proved that it can significantly increase the compression rate. Golomb-Rice can provide a simple way to increase compression rate by selecting a proper divider *K*. Golomb-Rice coding is one of the special form of Rice coding, where *K* can be written as $k=2^n$. Meanwhile due to the features of Golomb-Rice coding, PD_2 should be transformed into positive number *PD'* by the equation (3)

$$\mathrm{PD}'(\mathrm{n}) = \begin{cases} 2 \times PD_2(n), & PD_2(n) \geq 0 \\ 2 \times PD_2(n) + 1, & PD_2(n) < 0 \end{cases} \qquad (3)$$

Tri-entropy coding is going to combine the advantage of both two algorithms, the outcome from the predictor will go through two layers of Huffman coding, and one layer of Golomb-Rice coding by the frequency of occurrence. Fig.5 illustrates the tri-entropy coding rules.

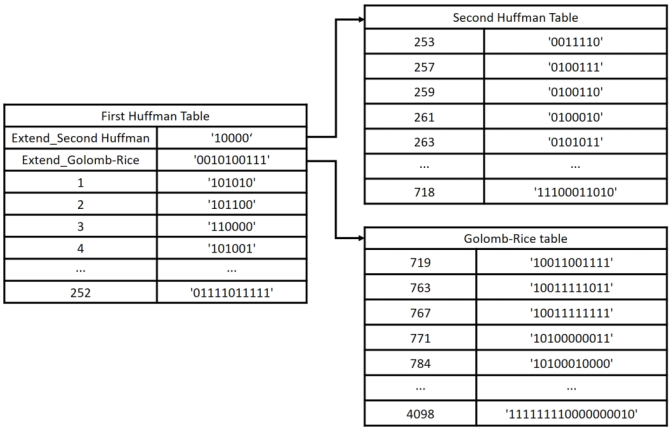


Fig.5 The proposed tri-entropy coding tables.

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III. Simulation Results

To evaluate the performance of the proposed lossless compression algorithm with previous studies, CHB-MIT Scalp EEG Database were selected as the test dataset. As show in Table.1, most of channels in this database gets higher CR rate. The average compression rate in CHB-MIT Scalp EEG Database is 2.37. Table.1 shows the comparison of compression rates and bit per sample in the proposed lossless compression algorithm with previous studies. As results shown, the proposed lossless compression algorithm has better performance than previous studies [1][2][3].

Table.1 Comparison of compression rates and bit per sample in the proposed lossless compression algorithm with previous studies

Channels	Slope [1]	Adaptive Trending [2]	Dynamic Voting [3]	This Study
1	1.69	1.73	1.98	2.09
2	1.88	1.96	2.27	2.23
3	1.89	1.97	2.31	2.25
4	2.13	2.27	2.65	2.51
5	1.63	1.67	1.87	2.04
6	2.07	2.15	2.48	2.37
7	2.35	2.43	2.74	2.66
8	2.08	2.21	2.56	2.44
9	1.73	1.76	1.96	2.11
10	2.27	2.35	2.67	2.55
11	2.38	2.47	2.74	2.73
12	1.83	1.97	2.44	2.37
13	1.66	1.74	2.02	2.09
14	1.75	1.84	2.18	2.17
15	1.94	2.03	2.38	2.30
16	1.79	1.92	2.35	2.32
17	2.54	2.6	2.86	2.92
18	2.58	2.63	2.87	2.99
19	1.89	1.97	2.31	2.56
20	1.77	1.87	2.18	2.18
21	1.92	1.96	2.26	2.26
22	1.95	2.04	2.4	2.31
23	1.94	2.03	2.38	2.30
Average	1.95	2.04	2.35	**2.37**
Bit per sample	8.21	7.84	6.81	**6.75**

Table. 2 shows energy consumptions for Bluetooth and Zigbee protocols by using the proposed lossless compression algorithm or not. It is clear to see that after data been compressed, the power consumption will be drop significantly.

Table.2 Energy consumptions for Bluetooth and Zigbee protocols

`	Bluetooth	Zigbee
Etx_original(nJ/bit)	143	296
Compression Rate	2.37	2.37
Etx_CR(nJ/bit)	60.34	124.89
Energy Saving(%)	57.80	57.80

IV. Conclusion

A lossless EEG compression hardware oriented algorithm based on a fuzzy decision, semi-supervised learning prediction function, voting prediction and tri-entropy coding technique is proposed. The proposed algorithm decreases data storage space, bandwidth of network and lower power consumption. In CHB-MIT Scalp EEG Database, this study achieved 2.37 compression rate, which is 0.85% better than [3]. The proposed algorithm was developed for hardware implementation, which is suitable for realizing on chip and using in WBSN system.

ACKNOWLEDGMENT

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