Implementation of VLSI Based Efficient Lossless EEG Compression Architecture using Verilog HDL

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Abstract. If in reality, electroencephalography signal data transfer through the Wireless Network is a frequently used device related to stability and performance problems. This study, the lossless EEG compression circuit architecture of an efficient VLSI device is suggested to increase both the capability of EEG signal transmission and reliability over WBAN. A new lossless data compression technique consisting of even a proposed neural prediction, a casting a vote solution and a quadra probability compression codec has been applied to the proposed architecture. The mid equilibrium encoder consists of a static coding table of multiple Binary Areas such as training encoders using the comparator and multiplexer’s fundamental components. Help boost the efficiency of the proposed system; a pipelining method was applied. Produce the suggested specification, a 0.18 m CMOS technology containing 8215 gates under 100 MHz clock speed under an operating environment. To test the usefulness of the suggested compression rate technique, for 25 channels, this results in a mean value of 2.35. This work accomplished a 9.6 % increase in compression rate and a 24.1 % decrease in processing costs relative to new competition equipment lossless EEG compressed designs, although keeping a constant interface simplicity.

Keywords: EEG, lossless EEG compression, Predicting code block, WBAN.

1. Introduction
Through the emergence of new surgical approaches, large quantities of evidence can now be Gathered from the nervous system, heart and tissues that live. Therefore, it has very necessary to locate and process the fundamental characteristics of those same signs to make it possible to express and interpret their properties more accurately [1]. Latest studies indicate that EEG is the most difficult calculation of electrograms to obtain from a hardware point of view. The frequency and characteristics of these signals produced by the brain may vary. Challenges facing the group of data analysis and EEG scientists are to identify and delete recorded items and analyze the electrical signals within. The memory chip occupies a substantial part of the chip region, and it is possible to minimize the cost by minimizing size. This is achieved by encoding, which minimizes usage as memory consumes a large power consumption for the signal processing device. The convergence of the VLSI Neural Signal Processor with compressed
systems results in high-performance Biological Transmission Side. In addition, to interface these devices with analogue signals, this article discusses modern bio trails that use method to optimize output with very difficult application domains. The corresponding biosignal processor block diagram describing the EEG signal processor utilizing an effective compressed technique [2-8] is shown in Fig 1. In this outline the structure, the whole commands are chosen, and each is given a trigger word. There are two steps involved. The initial programme instructions are compressed in the design process and then stored together with encoding tablesAs during the runtime stage; the actual orders are extracted from the compact versions, using the debugging table(s) using debugging firmware. In the next chapter, similar works from that kind of study are mentioned. The definition of the bio chart explains, and its design is addressed. Demonstrates the implementation and overall outcome task, the following Section ends and proposes future ventures or development in the sector.

The fundamental purpose of this research is to explore multiple approaches to image compression that have widely been applied to various medical images with an emphasis on brain images. These techniques are clarified, and objective comparisons are made with the benefits and drawbacks of these techniques. The demand for data storage space and bandwidth for transmission continues to surpass the technology available capacities. Picture compression is the method of obtaining a compressed representation of an image while preserving all the necessary details essential for medical diagnosis. Picture compression is simply a method of reducing the byte size of images that are stripped of dominance and accuracy. The reduction in size makes it possible to store extra images in a given volume of a disc to view in digital. The methods of image compression are commonly divided into two core types: methods of lossless and lossy.

2. Lossless Compression
With lossless compression techniques, high compression speeds cannot be accomplished due to signal randomness. Traditional compression algorithms such as TAR and ZIP can be used advanced algorithms to obtain higher compression ratios. The use of mathematical transformations is a common means of improving the compression ratio. The Karhunen-Loeve transform (KLT) approach for multichannel EEG compression is seen in [9-13]. Elevated calculation time is the key downside of KLT. The advanced fault simulation technique with lossless has been applied to improve compression efficiency. For context-based error modelling, another method is to use neural network predictors [14-16]. This showed some increase in the performance of compression by eliminating bias offset of raw data.

3. Lossy Compression
Lossy algorithms do not allow complete signal reconstruction, as opposed to lossless compression. The use of Wave Packet Transform [4] requires recent studies on lossy EEG compression. The use of the JPEG2000 based lossy EEG compression algorithm is proposed. The JPEG2000 algorithm is designed for image compression, but implementations are not limited to image files alone. Discrete Wavelet Transform quantization and Arithmetic Coder are the key components of the algorithm. The DWT substitutes the original JPEG format's Discrete Cosine Transform (DCT). A compression ratio of 11:1 can be accomplished using various compression parameters [17-19] In addition, recent experiments have been carried out based on wavelets. Such techniques have seen some increase in compression performance at the expense of computing cost. See for an efficiency survey of certain EEG compression techniques. Several compression methods have recently been published, but none of these techniques uses Discrete Cosine Transform or fast DCT algorithms for EEG data compression to the best of our knowledge. Example of impulse response plot shown in figure 1. This approach is acceptable for hardware deployment and should decrease computation time in embedded systems [20-21].
DCT is a method of transformation for the transformation of a time series signal into simple frequency components. The $f(x)$ DCT input is a set of $N$ data values, and the $Y(u)$ output is a set of the Discrete Cosine Transform's $N$ coefficients. The one-dimensional DCT is defined by the formula for a list of $N$ real numbers.

$$Y(u) = \sqrt{\frac{2}{N}} \cdot \alpha(u) \cdot \sum_{x=0}^{N-1} f(x) \cdot \cos \left( \frac{\pi \cdot (2x + 1) \cdot u}{2N} \right)$$

The first coefficient of $Y(0)$ is known as the coefficient of DC, and the remainder is known as the coefficient of AC [9]. The DC coefficient gives the mean value of the initial signals.

$$\alpha(u) = \begin{cases} \frac{1}{\sqrt{2}}, & u = 0 \\ 1, & u > 0 \end{cases}$$

These small quantities, usually down to 0, maybe coarsely quantized. Large values of $N$ consist of a few big sets of data. In this case, the question is that specific data item is usually not correlated with a large collection and thus result in a set of transition coefficients in which all coefficients are large. For most image compression systems using DCT, the function of $N = 8[7]$ is used. $4N$ multiplications are necessary to apply formulas (1) and (2) explicitly, so it is slow and impractical. A variety of fast DCT computing algorithms have been proposed to resolve this. These algorithms decrease the number of multiplications and additions, but normally limit the number of samples to $2^m$, where $m$ is a positive integer.
The Areas such as training algorithm scaling K value are calculated from learning rate WS of predictions. The standard deviations are Sales of assets probability coded to use the factor. Finally, for output, the encoded stream is packed into fixed spacing data chunks. DPCM approximation is partially capable of modelling redundant data amongst consecutive samples prediction code block shown in Figure 2. Correlation coefficients appear to centre and peak close to zero in the ensuing central trend. An effective K parameter can be calculated from this equation, so that ranges with small discrepancies. An example shows an encoding table for Golomb-Rice with a K parameter. Shorter code lengths prevail as smaller symbol values occur more frequently. Finally, a coded source for the output, seen in Fig. 3, holds all the details needed to recover the original signal from the decoder.

The normal total distribution after DPCM of prediction seen, which is usually consistent with an optimum K parameter. In earlier literature, however, it was shown [5]. By correctly defining a background model on which bias reduction can be carried out to return each approximation to zero, such specific constructs can be derived—later resulting in fewer forecast errors for each distribution, more optimal parameters of Areas such as training K can be determined. The described type is xk, and differences are defined between the specimens.

\[ d_i = x_{k-i} - x_{k-i-1} \]

For example, in an "always rising" any positive value appears to be short for a total study's basic Predictive control forecast. This tendency is applied further to both the DPCM forecast, and so this outcome is a shortened visual feature chain after Transfer of risks coding. Frequency Reductions A major drawback of the methodology mentioned so far is its high-performance lag from a device point of view. Ideally, it should be instantly seen on the touchscreen display after a physiological sample.
population is sensed. The delay is seen as the Flow scale factor, so only if the K variable or bias redundancy value also calculated with Transfer of Risks algorithm start to output. The calculation process for the K factor and bias reduction value to solve these problems but rather is carried out in accordance with [23] on the per scale.

An entropy coder of Golomb-Rice, seen in grey in Fig. 4, applies the coding table of Golomb-Rice for different K values. It determines the threshold and part, depending on the current Areas such as training K vector and source num pad error rate, and the outcome to level in a clock cycle. The performance packing device seems to be the endpoint of the pipeline that holds four Alternatives gives frames with multiple sensing inputs that have been packed as specimens are encoded into sub-blocks. Once all of the packets are filled, the queue quality is pushed into its exit path, along with an abbreviated data type ID about the physiological file system. A preference approach is implemented such that minimal output lag is obtained if one or more partitions are performed simultaneously.
4. Results
Table 1 reflects the current flow rate findings for the different sensing results as determined from numerical simulations and pass with thread tests. A typical laboratory demonstration setup obtained raw image pixel data for DOT, while raw ECG data were obtained from EEG Lab, shown in fig 5, 6. Total, given the range of methodologies, sample accuracy, available bandwidth and actual width, an average CR of 2.05 was obtained within each medical diagnostics type. Similarly, the Ecomp size of the antenna fuel consumption was obtained by dividing the mean power consumption of the main compression unit by the data traffic range. Provided the normalized energy consumption Etx calculations for industrial Ethernet.

![Real and Imagined Motion EEG Data](image)

Figure 6. real and imagined data

| Reference | Advantages/ methods | Results |
|-----------|---------------------|---------|
| [6]       | Slighter quantity of memory is required | Yields far smaller reconstruction errors |
| [7]       | Fast and reliable in case of preservation of image details | Computationally complex. The disparity of error boundary |
| Proposed  | Predicting coder    | Better compression without significant loss in signal fidelity than previous methods |

5. Conclusion
In this paper, the proposed solution was to apply data compression to the EEG data, the VLSI design of a simple structure lossless scientific data compress, the effects of which are seen in mat lab waveforms. Signal altering was used as a technique to maximize compression performance. Almost 30 per cent compression ratio was achieved. For contrast, the highest compression obtained using standardized compression programmes was about 36%, so the EEG compression approach was superior. 23 % and 17 % power savings can be accomplished using market transceiver ICs at this specified output. This dissertation represents an analysis to evaluate the figure of power consumption that can be accomplished by the high efficiency of a rational compression ratio efficiency low-complexity lossless data compression algorithm. It will be of concern in the future to drive back the boundaries of low.
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