Low Power Logarithmic Current-to-Digital Converter (CDC) Inspired by Molecular Genetic Processes for Biomedical Applications

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Keywords: Current to Digital Converter (CDC), Logarithmic ADC, Low Power, Subthreshold Analog Circuits, Neural Network, Bio-Inspired, Biomedical Applications, Adaptive Systems.

Abstract: A Bio-inspired low-power logarithmic Current-to-Digital Converter is presented. The main building block of the CDC is a computing unit named Perceptgene (PG) that was inspired by molecular biology and has training and computing capabilities in the log domain (Rizik et al., 2022). The Perceptgene which models a nonlinear molecular behavior was implemented using a translinear subthreshold electronic circuit (Oren et al., 2023). Thus the CDC design which uses the Perceptgene building block operates more naturally in the Log domain and is expected to consume low power which can make it usable for biomedical applications.

1 INTRODUCTION

The need to process biomedical signals using portable, wearable or implantable electronic devices has increased significantly in recent years. These devices are operated by minor batteries thus an energy-efficient ADC became a fundamental component. Biosensors are widely used in applications such as Glucose monitoring, DNA sequencing, food analysis, and microorganism analysis. Some of these biosensors, translate a biological marker that changes in the logarithmic scale (Thanachayanont, 2015) to a current output signal, thus a logarithmic CDC is a more natural readout device for them. In addition, a logarithmic ADC (Sit and Sarpeshkar, 2004) (Mahattanakul, 2005) (Rhew et al., 2014) (Sundarasaradula et al., 2016) (Danial et al., 2019) can perform analog-to-digital conversions with non-uniform quantization thus it can convert small signals with high resolution and large signals with coarse resolution, which enables handling large input dynamic range signals with a lower number of bits compared to a linear ADC. The lower number of bit results a lower power and smaller area. In this study, we propose ultra-low power electronic circuits inspired by gene networks to demonstrate the computational abilities of neuronal networks. This approach relies on insights we have gained that map neuronal networks to molecular biological systems (biomorphic (Rizik et al., 2022) (Daniel et al., 2013)) and then to electronic circuits (cytomorphic (Sarpeshkar, 2011) (Hanna et al., 2020)), as shown in (Fig. 1). Previously (Rizik et al., 2022) we proposed the perceptgene neural model that was inspired by molecular biology and implemented it (Oren et al., 2023) using a translinear (Gilbert, 1975) subthreshold electronic circuit that enables low-power computation at the log domain. **Implementing CDC using the perceptgene building block will enable more natural operation in the Log domain and ultra-low power consumption, thus will better suit biomedical systems.**

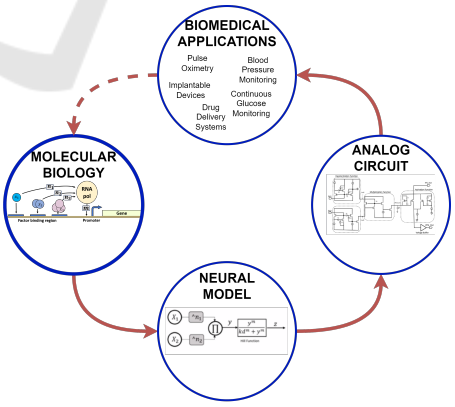

Figure 1: Neural model inspired by molecular biology and implemented by analog circuit for bio-medical applications.

This paper describes a new concept for implementing a logarithmic current to digital converter using PG building blocks.

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2 PERCEPTGENE BUILDING BLOCK

2.1 Bio-Molecular "Neuron"

Our neural model was inspired by combinatorial gene regulation kinetics of promoter activation (Fig. 2) . A combinatorial promoter is regulated by multiple transcription factors x_i, each transcription factor binds to its designated region and afterward participates in recruiting the RNA polymerase to form the activation complex. In our model, several biological parameters are involved, such as the biological cooperativity of proteins, the number of binding sites in the promoter, the protein quaternary structure, and the binding affinities of protein-protein/protein-DNA reactions. In this process, multiple transcription factors participate and bind upstream to a gene sequence. Together they facilitate the binding of RNA polymerase to the promoter region forming the activation complex that initiates gene transcription.

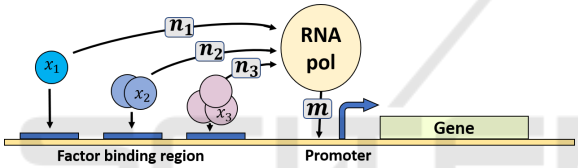

Figure 2: Anatomy structure of operating principles of gene regulatory network.

For a combinatorial activation, the relation between the transcription factors concentration and the promoter transcription rate, under certain conditions (Bintu, 2005), can be simplified and modeled as follows:

$$P = \frac{(\prod_i^N x_i^{n_i})^m}{(\prod_i^N x_i^{n_i})^m + kd^m} \quad (1)$$

Where P is the activation rate, x_i is the transcription factor concentration, n_i is the Hill coefficient of transcription factor i associated with the activation complex formation, m is the Hill coefficient for the binding of the activation complex with the promoter and kd is the dissociation constant for the complex binding with the promoter.

By applying a logarithmic transform to Eq. 1, we obtain a new abstract model (Fig. 3b) analogous to the perceptron model (Fig. 3a) that is used in artificial neural networks (Haykin, 2004) . Similar to other artificial neuron models that operate as binary classifiers, this model achieves classification via a weighted input integration followed by a threshold activation for the output. However, three notable differences exist. First, the weighing of the inputs is done here according to a power law and not multiplication. Second, the inputs are integrated via a product rather than a summation. And third, the activation function used for this model is the Hill equation instead of the standard logistic function. Interestingly the perceptgene model can be viewed as a perceptron with a log transform over its input dynamic range, the proof is straightforward from the following equality:

$$P = \frac{(\prod_i^N x_i^{n_i})^m}{(\prod_i^N x_i^{n_i})^m + kd^m} = \frac{e^{m\sum_i^N n_i Ln(x_i)}}{e^{m\sum_i^N n_i Ln(x_i)} + e^{mLn(kd)}} \quad (2)$$

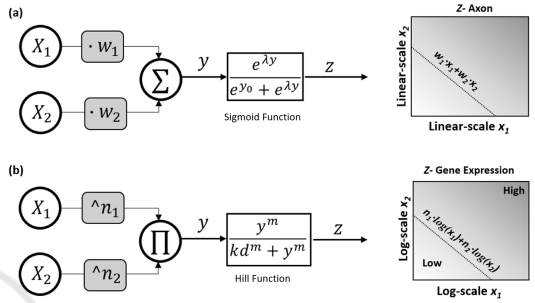

Figure 3: Abstract artificial intelligence models for (a) perceptron inspired by neural networks: x_i are the inputs, w_i are multiplicative weights, input integration is done via summation, and the activation function is the sigmoid function. Depicted on the right is the resulting linear separable classification of the analog inputs x1 and x2 (b) perceptgene inspired by genetic networks: x_i are the inputs, n_i are power weights, input integration is done via a product, and the activation function is the Hill equation. Depicted on the right is the resulting logarithmically separable classification of the analog inputs x1 and x2.

2.2 Perceptgene Circuit Design

After the perceptgene circuit was implemented as described in detail at (Oren et al., 2023), the main goal was moving from ideal structures to real devices which can be implemented in silicon. The voltage divider of the power circuit which requires huge Giga ohms resistors was a significant challenge and it was decided to implement it using two capacitors that are connected in series as can be viewed at the exponential function circuit in Fig. 4. The disadvantage of this implementation compared to regular resistors is the need to deal with the dynamic behavior of the divider. A slight change in the values of these capacitors will enable tuning the binary weights as required.

In order to implement the CDC's voltage digital output, we had to convert the output current signals of the original perceptgene to a voltage signal. This was achieved by the digital buffer added at the output of the activation function as can be viewed in Fig. 4. The activation function with the output buffer operates as

a current comparator with a threshold that can be set by Ikd current.

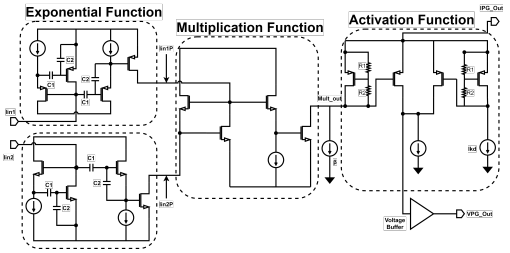

Figure 4: Perceptgene circuit building block.

3 LOGARITHMIC CDC: CONCEPT AND ARCHITECTURE

3.1 CDC Basic Concept

A 3-bit logarithmic CDC was designed using three perceptgenes cells. The architecture of the CDC can be viewed in Fig. 5 below. The input current is fed to the three PG units and an output digital code representing the value of the input current in the log domain is generated at the voltage outputs D0, D1, D2. The output code is calculated based on the reference current of each unit (Irefi) while taking into account a feedback value from higher bits. The weight for each input is marked as nij.

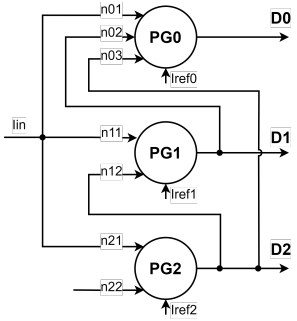

Figure 5: Perceptgene-based Log CDC architecture.

The perceptgene modeled in Fig. 3b can be written as a sigmoid (Eq. 2) that operates on the Log of the input Ii as follows:

$$PGi = \frac{e^{m\sum_i^N n_i Ln(I_i)}}{e^{m\sum_i^N n_i Ln(I_i)} + e^{mLn(Ikd)}} \quad (3)$$

For N=3, Kd=1, m=1, the sigmoid (Eq. 3) transition points for the PGi units in Fig. 5 are given by

$$\ln(I_{in}) \cdot n21 + \ln(I_2) \cdot n22 - \ln(I_{ref2}) = 0 \quad (4)$$

$$\ln(I_{in}) \cdot n11 + \ln(I_2) \cdot n12 - \ln(I_{ref1}) = 0 \quad (5)$$

$$\ln(I_{in}) \cdot n01 + \ln(I_2) \cdot n02 + \ln(I_3) \cdot n03 - \ln(I_{ref0}) = 0 \quad (6)$$

The required weights nij should be as in Fig. 6 and will be explained for each of the CDC bits.
For bit D2 (MSB), the transition at the CDC output is defined by Eq.4. Since no feedback from the previous stage and since the detected input should be 0.5 of the Max input logarithmic value:

$$ln(I_2) = 0, \quad ln(I_{in}) = 0.5 \cdot ln(I_{max})$$

Therefore the reference value should be :

$$\implies ln(I_{ref2}) = 0.5 \cdot ln(I_{max}) \quad (\text{for } n21, n22 = 1)$$

For bit D1, the transition at the CDC output is defined by Eq.5. In case no feedback from a higher bit (D2), the detected input should be 0.25 of the Max input logarithmic value and therefore the reference value should be:

$$\implies ln(I_{ref1}) = 0.25 \cdot ln(I_{max}) \quad (\text{for } D1 = 0)$$

If the higher bit (D2) is high, the detected input should be 0.75 of the Max input logarithmic value. Therefore, the current on the second input should be:

$$\implies n11 \cdot ln(I_2) = -0.5 \cdot ln(I_{max})$$

For bit D0 (LSB), the transition at the CDC output is defined by Eq.6. In case no feedback from higher bits (D1, D2), the detected input should be 0.125 of the Max input logarithmic value and therefore the reference value should be:

$$\implies ln(I_{ref0}) = 0.125 \cdot ln(I_{max}) \quad (\text{for } D1, D2 = 0)$$

If the higher bits (D1, D2) are 1, the detected input should be 0.875 of the Max input logarithmic value and therefore the current on the second and third inputs should be :

$$\implies n02 \cdot ln(I_2) = -0.25 \cdot ln(I_{max})$$
$$\implies n03 \cdot ln(I_3) = -0.5 \cdot ln(I_{max})$$

3.2 CDC Practical Topology

Implementing the above equations required using an architecture with negative weights and a perceptgene with 3 inputs which complicates the design significantly. Yet, an input with a negative weight can be replaced by an input with a positive weight which multiplies Iref as can be viewed in the following equations:

$$y = \frac{Iin^1 * x_2^{-0.5} * I_3^{-0.25}}{I_{ref}^{0.125}} \quad (7)$$

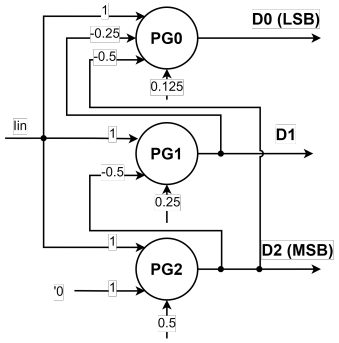

Figure 6: Basic topology of 3 bits CDC.

$$y = \frac{I_{in}^{1}}{I_{ref}^{0.125} * I_{2}^{0.5} * I_{3}^{0.25}}$$

Following the above changes, the updated architecture of the CDC can be viewed in Fig. 7. In this architecture, the feedback from higher bits was integrated into the Iref input, thus enabling the use of the original perceptgene building block which includes only 2 inputs with positive weights. The second input of the PG is the Ith, which has the value of the activation function's threshold; thus, when Iin equals Irefi, the multiplication output value is Ith which causes a transition in the activation function.

In addition to the above changes, the weights were normalized, and binary weight values were used since the implementation of binary weights is more simple than fraction weight implementation. The updated architecture of the CDC is close to SAR CDC as the outputs are impacting the reference (and not the inputs as in Pipe CDC). In contradiction to the SAR, the digital outputs are not converted by a full DAC but bit by bit.

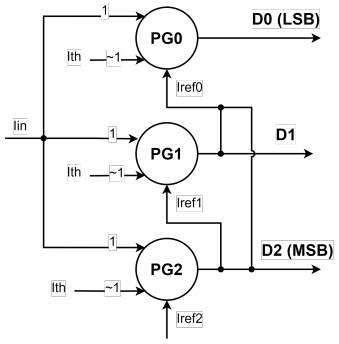

Figure 7: Final CDC topology.

3.3 CDC Circuit Design

The top-level block diagram of the CDC can be viewed in Fig. 8. The input current signal Iin is sampled and then mirrored in each of the three perceptgene blocks. The digital voltage is generated by each perceptgene based on its reference current (Irefi) and sampled by FlipFlop. The main current sources include the reference current source Iref2 and the switched reference current sources Iref1, Iref0. The currents on these current sources are being set by external bias voltages Vrefi as can be viewed in this Figure.

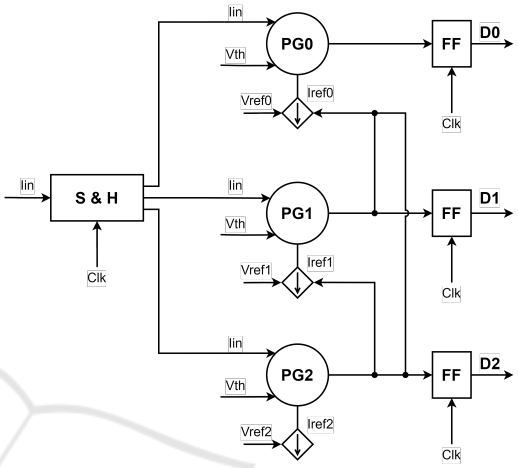

Figure 8: CDC Top level block diagram.

The CDC block diagram in Fig. 8 was implemented using 180nm technology. We decided to implement a 10-base logarithmic CDC but the design can be easily changed to another logarithmic base. The minimum input current is 100pa and the maximum is 1uA, thus requiring only 6 out of the 8 codes as can be viewed in Table. 1 below. We could use a serial architecture where the CDC bits are generated serially by one perceptgen block but we preferred for simplicity the parallel 3 perceptgene architecture.

Table 1: CDC inputs currents and output codes.

D2 (MSB)	D1	D0 (LSB)	Iin
0	0	0	0pA
0	0	1	100pA
0	1	0	1nA
0	1	1	10nA
1	0	0	100nA
1	0	1	1uA

Spice simulations were run in order to check the CDC basic functionality. DC simulation results of the CDC outputs changing due to input current ramp can be viewed in Fig. 9(a). The code is changing between 000 to 101 as the input current changes in logarithmic steps from 10pA to 1uA.

Simulation of a sinus signal in the log domain re-

quires inserting a current waveform which is an exponential signal. Such signal can be viewed in Fig. 9b(1) and the waveform in the log domain which is a pure sinus in Fig. 9b(2).

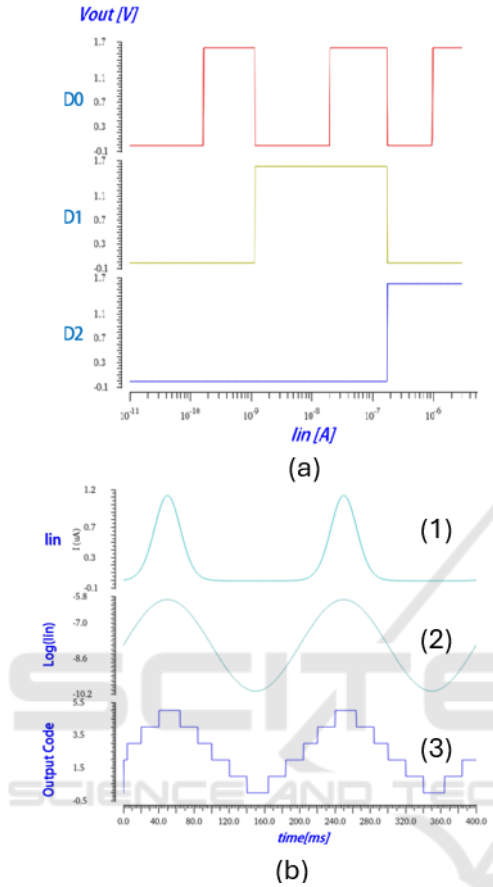

Figure 9: Basic functional simulations: (a) DC simulation of output signals as a function of input ramp current (b) Transient simulation of output constructed code as a function of input exponential signal.

Since the CDC converts the logarithmic value of the input current signal to digital code, the expected output signal which is constructed by such code should be a sinus wave. Such sinus signal can be viewed in Fig. 9b(3)

4 CONCLUSIONS

We propose a novel concept for implementing a logarithmic CDC based on a perceptgene building block inspired by molecular biology. Using perceptgene as a building block makes the CDC modular and with the potential for ANN-like training capability. The modular and flexible architecture enables simple scaling of the design for the required numbers of bits and different logarithmic bases. The perceptgene was designed using subthreshold translinear analog circuits that guarantee a low power consumption. Implementation of the CDC circuits using perceptgene building block in 180nm technology demonstrates the required basic functionality and serves as proof of the concept. The proposed low-power modular logarithmic CDC might be usable for several biomedical applications.

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