

A Log-Domain Implementation of the Diffusion Network in Very Large Scale Integration

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Abstract

The Diffusion Network(DN) is a stochastic recurrent network which has been shown capable of modeling the distributions of continuous-valued, continuous-time paths. However, the dynamics of the DN are governed by stochastic differential equations, making the DN unfavourable for simulation in a digital computer. This paper presents the implementation of the DN in analogue Very Large Scale Integration, enabling the DN to be simulated in real time. Moreover, the log-domain representation is applied to the DN, allowing the supply voltage and thus the power consumption to be reduced without limiting the dynamic ranges for diffusion processes. A VLSI chip containing a DN with two stochastic units has been designed and fabricated. The design of component circuits will be described, so will the simulation of the full system be presented. The simulation results demonstrate that the DN in VLSI is able to regenerate various types of continuous paths in real-time.

1 Paper Body

In many implantable biomedical microsystems [1, 2], an embedded system capable of recognising high-dimensional, time-varying signals have been demanded. For example, recognising multichannel neural activity on-line is important for implantable brain-machine interfaces to avoid transmitting all data wirelessly, or to control prosthetic devices and to deliver bio-feedbacks in realtime [3]. The Diffusion Network (DN) proposed by Movellan is a stochastic recurrent network whose stochastic dynamics can be trained to model the probability distributions of continuous-time paths by the Monte-Carlo Expectation-Maximisation (EM) algorithm [4, 5]. As stochasticity is useful for generalising the natural variability in data [6, 7], the DN is further shown suitable for recognising noisy, continuous-time biomedical data [8]. However, the stochastic dynamics of the DN is defined by a set of continuous-time, stochastic differential equations (SDEs). The speed

of simulating stochastic differential equations in a digital computer is inherently limited by the serial processing and numerical iterations of the computer. Translating the DN into analogue circuits is thus of great interests for simulating the DN in real time by exploiting the natural, differential current-voltage (I-V) relationship of capacitors [9]. This paper presents the implementation of the DN in analogue Very Large Scale Integration (VLSI). To minimise the power consumption, the power supply voltage is only 1.5V, and most transistors are operated in subthreshold regions. As the reduced supply voltage limits directly the dynamic range available for voltages across capacitors, the log-domain representation proposed in [10] is applied to the DN, allowing diffusion processes to be simulated in a limited voltage ranges. After a brief

introduction to the DN, the following sections will derive the log-domain representation of the DN and describe its corresponding implementation in analogue VLSI.

$x_j(t) = \exp\left(-\frac{1}{C_j} \int_0^t \left(\sum_{i=1}^n x_i(t) + I_j \right) dt\right)$

Figure 1: The architecture of a Diffusion Network with one visible and two hidden units

The block diagram of a DN unit in VLSI is shown in Figure 2. The block diagram consists of a summation node, a capacitor block, an exponential block, and a current source. The summation node takes inputs from the visible unit and two hidden units. The output of the summation node is integrated by the capacitor block. The output of the capacitor block is then passed through an exponential block to produce the final output current I_j .

Figure 2: The block diagram of a DN unit in VLSI

The Diffusion Network

As shown in Fig. 1, the DN comprises n continuous-time, continuous-valued stochastic units with fully recurrent connections. The state of the j th unit at time t , $x_j(t)$, is governed by

$$C_j \frac{dx_j(t)}{dt} = -x_j(t) + I_j$$

(1)

where $\mu_j(t)$ is a deterministic drift term given in (2), σ a constant, and $dB(t)$ the Brownian motion. The Brownian motion introduces the stochasticity, enriching greatly the representational capability of the DN [5].

$n \times X$

$$\mu_j = \sum_{i=1}^n w_{ij} x_i(t) + \mu_j + \sigma \sum_{i=1}^n x_i(t) + \sigma \sum_{i=1}^n x_i(t) + \sigma \sum_{i=1}^n x_i(t) + \sigma \sum_{i=1}^n x_i(t)$$

w_{ij} defines the connection weight from unit i to unit j . and μ_j represent the input capacitance C_j and transmembrane resistance, respectively, of the j unit. μ_j is the input bias, and σ is the sigmoid function given as $\sigma(x_j; a) = \frac{1}{1 + e^{-ax_j}}$ where a adapts the slope of the sigmoid function. As shown in Fig. 1, the DN contains both visible(white) and hidden(grey) stochastic units. The learning of the DN aims to regenerate at visible units the probability distribution of a specific set of continuous paths. The number of visible units thus equals the dimension of the data to be modeled, while the minimum number of hidden units required for modeling data satisfactorily is identified by experimental trials. During training, visible units are clamped to the dynamics of the training dataset, and the dynamics of hidden units are Monte-Carlo sampled for estimating optimal parameters (w_{ij} , μ_j , σ_j , μ_j) that maximise the expectation of training data [5]. After training, all units are given initial values at $t = 0$ only to sample the dynamics modeled by the DN. The similarity between the dynamics of visible units and those of training data indicate how well the DN models the data. 2.1

Log-domain translation

To maximise the dynamic ranges for diffusion processes in VLSI, the stochastic state $x_j(t)$ is represented as a current and then logarithmically-compressed into a voltage VX_j in VLSI [11]. The logarithmic compression allows $x_j(t)$ to change over three decades within a limited voltage range for VX_j . The voltage representation VX_j further facilitates the exploitation of the nature, differential (I-V) relationship of a capacitor to simulate SDEs in real-time and in parallel.

2

The logarithmic relationship between $x_j(t)$ and VX_j can be realised by the exponential I-V characteristics of a MOS transistor in subthreshold operation [12]. To keep $x_j(t)$ a non-negative value (current) in VLSI, an offset x_{off} is added to $x_j(t)$, resulting in the following relationship between $x_j(t)$ and VX_j .

(4)

where I_s and β are process-dependent constants extractable from simulated I-V curves of transistors. Substituting Eq. (4) into Eq. (1) then translates the diffusion process in Eq. (1) into the following equation.

$\sum_{i=1}^n dVX_j + \beta VX_j CX_j = \mu_j + \sum_{i=1}^n w_{ij} x_i(t) + \sigma \sum_{i=1}^n x_i(t) + \sigma \sum_{i=1}^n x_i(t) + \sigma \sum_{i=1}^n x_i(t)$ (5) where CX_j equals C_j/V_j . Fig. 2 illustrates the block diagram for implementing Eq. (5) in VLSI. CX_j is a capacitor and VX_j the voltage across the capacitor. Each term on the right hand side of Eq. (5) then corresponds to a current flowing into CX_j . Let $(V_P - V_N)$ and I_{VAR} represent the differential input voltage and the input current of an EXP-element,

respectively. Each EXP-element in Fig. 2 produces an output current of $I_{out} = I_V A_R \exp(V_P - V_N)$. Therefore, the EXP-elements implement the first three terms multiplied with $\exp(V_X)$ in accordance with Eq. (5). The last term, I_{IS} , is a constant and is thus implemented by a constant current source. Finally, the Pnsigmoid circuit transforms x_j into $\sigma(x_j)$ and the multipliers output a total current proportional to $\sum_{i=1}^n \sigma(x_i)$.

7 6 5 4 3 0
100
200 300 Time samples
400
500
0 100 200 300 400 500 600 700 800 900 1000 Time samples

Figure 3: The stochastic dynamics (gray lines) regenerated by the DN trained on the bifurcating curves (black lines).

Figure 4: The stochastic dynamics (gray lines) regenerated by the DN trained on the sinusoidal curve (the black line). 10 9 8 Unit 2

7.5 6.5 5.5 4.5 3.5 2.5
6 5 4
0
20
40 Time samples
60
80

Figure 5: The stochastic dynamics (gray lines) regenerated by the DN trained on the QRS segments of electrocardiograms (black lines). 2.2

7
3.5
4.5
5.5 6.5 Unit 1
7.5
8.5

Figure 6: The stochastic dynamics (gray lines) regenerated by the DN trained on the handwritten 'a' (the black line).

Adapting τ_j instead of τ_j

The DN has been shown capable of modeling various distributions of continuous paths by adapting w_{ij} , τ_j , and τ_j in [5]. An adaptable τ_j corresponds to an adaptable CX_j , but a tunable capacitor with a wide linear range is not easy to implement in VLSI. As Eq. (2) indicates that τ_j is complementary

to τ_j in determining the 'time constant' of the dynamics of the unit j , the possibility of adapting τ_j instead of τ_j is investigated by Matlab simulation. With $\tau_j = 1$, the DN was trained to model different data by adapting τ_{ij} , τ_j , and τ_j for 100 epochs. A DN with one visible and one hidden units was proved capable of regenerating the dynamics of bifurcating curves (Fig. 3), sinusoidal waves (Fig. 4), and electrocardiograms (Fig. 5). Moreover, a DN with only two visible units was able to regenerate the handwritten 'a' satisfactorily, as illustrated in Fig. 6. The promising results supported the suggestion that

adapting $I_{j,0}$ instead of $I_{j,1}$ also allowed the DN to model different data. As a variable $I_{j,0}$ simply corresponded to a tunable current source $I_{j,0}$ IS in Fig. 2, the VLSI implementation was greatly simplified. 2.3

Parameter mappings

Table 1 summarises the parameter mappings between the numerical simulation and the VLSI implementation. All variables except for V_{Xj} in Fig. 2 are represented as currents in VLSI. The unit currents (I_{unit}) of x_j , I_{ij} , and $I_{j,0}$ are defined as 10 nA to match the current scales of transistors in subthreshold operation, as well as to reduce the power consumption. Moreover, extensive simulations indicate that the dynamic ranges required for modeling various data are $[10^{-3}, 5]$ for x_j and $[10^{-30}, 30]$ for I_{ij} . With $x_{off} = 5$ in Eq. (4), i.e. $x_{off} = 50$ nA in VLSI, V_{Xj} ranges from 773 to 827 mV. While the diffusion process in Eq. (1) is iterated with $\Delta t = 0.05$ in numerical simulation, $\Delta t = 0.05$ is set to be 5 μ s in VLSI, corresponding to a reasonable sampling rate (200kHz) at which most instruments can sample multiple channels(units) simultaneously. Finally, the unit capacitance for $1/I_{j,0}$ is calculated as $C_{unit} = I_{unit} \cdot \Delta t_{unit} / V_{Xj,unit}$, equaling 1 pF and resulting in $C_{Xj} = C_{unit} = 30$ pF. Table 1: Parameter mappings between numerical simulation and VLSI implementation parameter

x_j	x_{off}	V_{Xj}	$I_{j,0}$	I_{ij}	C_{Xj}	Δt
numeric	-3 to 5	0.773 to 0.827	-30 to 30	-1 to 1	$I_{j,0} = 30$	0.05 to 0.5
circuit	-30 to 50 nA	50 nA	773 to 827 mV	-300 to 300 nA	-400 to 400 nA	30 pF to 5 μ s
comment $I_{unit} = 10$ nA offset term in Eq. (4) $V_{Xj,unit} = 1$ V $I_{unit} = 10$ nA activation function $C_{unit} = 1$ pF $t_{unit} = 0.1$ ms						

Circuit implementation

A DN with two stochastic units have been designed with the CMOS 0.18 μ m technology provided by the Taiwan Semiconductor Manufacturing Company (TSMC). The following subsections introduce the design of each component circuit. 3.1 The EXP element Fig. 7(b) shows the schematics of the EXP element. With M1 and M2 operated in the subthreshold region, the output current is given as

$I_{out} = I_{B,0} \exp(n V_{GS} / V_T)$ where V_T denotes the thermal voltage and n the subthreshold slope factor. Comparing Eq. (6) with Eq. (4) reveals that $\beta = 1/n V_T$. As the drain current (I_d) of a transistor in subthreshold operation is exponentially proportional to its gate-to-source voltage (V_{GS}) as $I_d = I_{B,0} \exp(n V_{GS} / V_T)$, $\beta = 1/n V_T$ is extracted to be 30 by plotting $\log(I_d)$ versus V_{GS} in SPICE. Transistors M3-M5 form an active biasing circuit that sinks $I_B + I_{out}$. By adjusting the gate voltage of M3 through the negative feedback, I_{out} is allowed to change over several decades. In addition, 4

IOU T
VP VN
M7
IOU T
EXP
0 IOU T

IB
 VN
 VP M1
 IB
 0 IOU T
 IB
 IOU T
 IB M5
 IV AR

n actually depends on the gate voltage and introduces variability to β [13]. To prevent the variable β from introducing simulation errors, all EXP elements of the DN unit are biased with a constant $IB = 100$ nA. As shown by Fig. 7(a), I_{out} of each element is then re-scaled by the one-quadrant 0 current multiplier basing on translinear loops (Fig. 7(c)) [13] to produce $I_{out} = I_{out} \beta IV AR / IB$, where $IV AR$ represents the current input to each element in Fig. 2 (e.g. I_{out} or I_{out}).

IV AR
 M2
 M3
 M4
 M1 VS M2
 Vbiasn
 Vbiasn Vref
 M4
 M6
 M3
 (a)
 M5
 (b)
 (c)

Figure 7: The circuit diagram of the EXP element.

3.2

Current multipliers

Four-quadrant multipliers basing on translinear loops [13] are employed to calculate I_{ij} (x_i) in Eq. (5). Both I_{ij} and (x_i) are represented by differential currents as

$$I_{ij} = I_{+} + I_{-}, (x_i) = I_{+} - I_{-} \quad (7)$$

Let the differential current $(I_{+} - I_{-})$ represents the multiplier's output and I_U represent a unit current. Eq. (8) indicates that the four-quadrant multiplication can be composed of four one-quadrant multipliers in Fig. 7(c), as illustrated in Fig. 8.

$$I_{+} - I_U - I_{-} - I_U = (I_{+} - I_{+} + I_{-} - I_{-}) (I_{+} - I_{-} + I_{-} - I_{+}) \quad (8)$$

$$I_{+} - I_U$$

IZ?

Figure 8: The four-quadrant current multiplier 5

I??

IZ+

IU I?+

IU I??

I?+

IU

I??

I?+

I??

Fig. 9 shows the simulation result of the four-quadrant multiplier, exhibiting satisfactory linearity over the dynamic ranges required in Table 1.

(IZ+ ? IZ?) in nA

500

= ?400nA = ?300nA = ?200nA = ?100nA

300

100 0 ?100

?i ?i ?i ?i

?200 ?400

= = = =

?200

gain=0.8 gain=1.0 gain=3.0 gain=5.0

400 Output current in nA

?i ?i ?i ?i

200

?i = 0 100nA 200nA 300nA 400nA

200 100 0 -100 -200 -300 -400

0

200

-500 -600

400

-400

-200 0 200 Input current in nA

(I?+ ? I??) in nA

Figure 9: The simulation results of the fourquadrant current multiplier 3.3

400

600

Figure 10: The simulation result of the sigmoid circuit with different Va

Sigmoid function ?(?)

Fig. 11 shows the block diagram for implementing the sigmoid function in Eq. (3). The current I_{Xi} representing x_i is firstly converted into a voltage V_i by the the operational amplifier(OPA) with a voltage-controlled active resistor (VCR) proposed in [14]. V_i is then sent to an operational transconductance amplifier(OTA) in subthreshold operation, producing an output current of $I_s = I_B \tanh$

$$\frac{1}{2nUT} (V_i - V_{ref}) \quad (9)$$

Since $V_i - V_{ref} = R_i \cdot I_{xi}$, with R_i representing the resistance of the VCR, the voltage V_a adapts R_i and thus the slope of the sigmoid function. Finally, the 2nd generation current conveyor (CCII) in Fig. 12 [15] converts the current I_s into a pair of differential currents (I_{OUTN} , I_{OUTP}) ranging between -400 nA and $+400$ nA. The differential currents are then duplicated for the inputs of four-quadrant multipliers of all DN units. V_a

VCR
 I_{xi}
 I_{OUTP} OPA V_{ref}
 CCII
 OTA V_{ref}
 I_{OUTN}
 V_{ref}

Figure 11: The block diagram of the sigmoid circuit.

3.4 Capacitor amplification As $C_{Xi} = 30$ pF requires considerable chip area, C_{Xi} is implemented by the circuit in Fig. 13, utilising the Miller effect to amplify the capacitance. Let A denote the gain of the amplifier. The effective capacitance between X and Y is $(1 + A) \cdot C_X$. Fig. 13 also shows the schematics of the amplifier whose gain is designed to be 2. As a result, $C_X = 10$ pF is sufficient for providing an effective C_{Xi} of 30 pF.

VBIAS
 C_X VREF
 X
 $4/4 \times 16$
 M1
 X
 $\frac{1}{2}A$
 Y
 $Y \ 4/4 \times 1$
 $C_{EQ} = C_X (1 + A)$
 M2

Figure 13: The circuit diagram of the capacitor amplified by the Miller effect.

6

Vbiasp 1.2V
 IP
 I_{OUTN}
 I_{sig} 0.3V
 VY
 VX
 1.2V
 IN
 OPA
 VREF
 I_{OUTP} Vbiasn 0.3V

Figure 12: The circuit diagram of the single-to-differential current conveyor

Technology

1P6M 0.18 μ m CMOS

Power Supply

1.5 Volts

Power Consumption

345 μ Watts

Num. of Units

2

1.368 \times 1.368mm²

Chip Area

(including pads)

Capability

1D/2D continuous paths

Max. Bandwidth

1.6 kHz

Figure 14: The chip layout and its specification.

55 50

IX1 in μ A

IX1 in μ A

50 40 30

45 40 35 30

0

0.5

1

1.5

2

0

Time in ms

0.05

0.1

0.15

0.2

0.25

0.3

Time in ms

Figure 16: The electrocardiogram dynamics regenerated by the DN chip in post-layout simulation (10 trials).

Figure 15: The sinusoidal dynamics regenerated by the DN chip in post-layout simulation (10 trials). 7

70 60

IX2 in μ A

50

IX1 in μ A

60 50 40

40 30 20

30
10 10 15 20 25 30 35 40 45 50 55
20 0
0.5
1
1.5
2
2.5
IX1 in μ A
Time in ms

Figure 17: The bifurcating dynamics regenerated by the DN chip in post-layout simulation (8 trials).

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Figure 18: The handwritten π regenerated by the DN chip in post-layout simulation (10 trials).

The Diffusion Network in VLSI

Fig. 14 shows the chip layout of the log-domain implementation of the DN with two stochastic units, so is the specification shown. The area of the core circuit and the capacitors are 0.306 mm² and 0.384 mm², respectively. The total power consumption is merely 345 μ W, by the merit of low supply voltage (1.5V) and subthreshold operation. The chip has been taped out for fabrication with the CMOS 0.18 μ m Technology by the TSMC. The post-layout simulations are shown in Fig. 15-18 and described as follows. With one unit functioning as a visible unit and the other as a hidden unit, the parameters of the DN was programmed to regenerate the one-dimensional paths in Sec. 2.2. The noise current $i_n = \sqrt{2qI_n} \text{ dB/dt}$ was simulated by a piecewise-linear current source with random amplitudes in the SPICE. As shown by Fig. 15-17, the visible unit was capable of regenerating the sinusoidal waves, the electrocardiograms, and the bifurcating curves with negligible differences from Fig. 3-5. Moreover, as both units functioned as visible units, the DN was capable of regenerating the handwritten π as Fig. 18. These promising results demonstrate the capability of the DN chip to model the distributions of different continuous paths reliably and power-efficiently. After chip is fabricated in August, the chip will be tested and the measurement results will be presented in the conference.

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Conclusion

The log-domain representation of the Diffusion Network has been derived and translated into analogue VLSI circuits. Based on well-defined parameter mappings, the DN chip is proved capable of regenerating various types of continuous paths, and the log-domain representation allows the diffusion processes to be simulated in real-time and within a limited dynamic range. In other words, analogue VLSI circuits are proved useful for solving (simulating) multiple SDEs in real-time and in a power-efficient manner. After verifying the chip functionality, a DN chip with a scalable number of units will be further developed for recognising multi-channel, time-varying biomedical signals in implantable microsystems. Acknowledgments The authors thank National Chip

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