Hardware ODE Solvers Using Stochastic Circuits

Siting Liu and Jie Han

Department of Electrical and Computer Engineering University of Alberta Edmonton, AB, Canada



□ Introduction to stochastic computing

• Stochastic integrators

□ Formulation of stochastic integrators

□ Proposed stochastic ODE solver design

- Nonhomogeneous ODEs
- Systems of ODEs
- Higher-order ODEs
- □ Error assessment and error reduction schemes
- □ Hardware evaluation and performance comparison
- **Conclusion and future work**

Introduction

□ In stochastic computing (SC), information is encoded and processed by random binary bit streams.



Stochastic Integrator



Function of a stochastic integrator: $seq_{out} \approx \int (a - b)dt$

An example of stochastic integrator (*N*=8)

i	a _i	b _i	Ci	RN _i	seq _{out}
0	1	0	$(0.1000000)_2$	0.75	0
1	1	1	$(0.1000001)_2$	0.20	1
2	0	1	$(0.1000001)_2$	0.19	1
3	0	0	$(0.1000000)_2$	0.62	0
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$$c_{i+1} = \begin{cases} c_i + 1/2^N & a_i = 1 \& b_i = 0\\ c_i - 1/2^N & a_i = 0 \& b_i = 1\\ c_i & a_i = b_i \end{cases}$$

$$c_{i+1} = c_i + \frac{1}{2^N} (a_i - b_i).$$
(1)

Accumulating (1) for i = 0, 1, 2, ..., k - 1

$$c_k = c_0 + \frac{1}{2^N} \sum_{i=0}^{k-1} (a_i - b_i) .$$
 (2)

Taking the expectation of (2)

$$\mathbb{E}[c_k] = c_0 + \frac{1}{2^N} \sum_{i=0}^{k-1} (\mathbb{E}[a_i] - \mathbb{E}[b_i]). \quad (3)$$

[Saraf et al., DATE 2014]

Unbiased Euler Solution Estimator

Euler
Method:
$$\frac{dy(t)}{dt} = f(t) \underbrace{\int_{h}^{y_{i+1}} (f(t))_{h}}_{h} (4)$$

$$\hat{y}_{i+1} = y_i + hf(t_i), (4)$$
where *h* is the step size and $t_i = h \cdot i$.
(4) can be changed to:

$$\hat{y}_{i+1} = y_i + hf(hi) \approx y(h(i+1)). (5)$$
By accumulating (5) for $i = 0, 1, 2, ..., k$

$$\hat{y}_k = y_0 + h \sum_{i=0}^{k-1} f(hi) \approx y(hk). (6)$$



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Stochastic Solvers for Nonhomogeneous ODEs



Stochastic Solvers for Systems of ODEs



A stochastic ODE solver for (10).

Hardware solution produced by stochastic ODE solver vs. analytical solution.

Higher-order Stochastic ODE Solvers



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Error Assessment of a Stochastic Integrator

$$\mathbb{E}[c_k] = c_0 + \frac{1}{2^N} \sum_{i=0}^{k-1} \mathbb{E}[(\boldsymbol{a_i} - \boldsymbol{b_i})] = \hat{y}_k \approx y(\frac{k}{2^N}).$$

Error of Euler method

• Reduced by using a smaller step size, i.e., increase the size of counter N.

Random fluctuation of stochastic circuits

- The use of low-discrepancy (LD) sequences can reduce random fluctuation.
- Sharing RNGs for generating the inputs of the stochastic integrator can also reduce the variance.



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Hardware Evaluation and Performance Comparison

ODE	Metric	SC	Binary*	Improvement
(8)	Energy/Operation (fJ)	144.49	201.05	28%
	Throughput/Area (solution/ $\mu s/\mu m^2$)	13.84	3.86	258%
	Minimum runtime (ns)	104.96	263.68	60%
(9)	Energy/Operation (fJ)	186.10	253.05	26%
	Throughput/Area (solution/ $\mu s/\mu m^2$)	9.76	0.94	934%
	Minimum runtime (ns)	104.96	586.24	82%
(10)	Energy/Operation (fJ)	201.21	466.00	56%
	Throughput/Area (solution/ $\mu s/\mu m^2$)	4.75	0.58	716%
	Minimum runtime (ns)	2573.59	8557.20	70%
(11)	Energy/Operation (fJ)	156.04	591.62	74%
	Throughput/Area (solution/ $\mu s/\mu m^2$)	5.68	0.44	1184%
	Minimum runtime (ns)	1597.44	6819.84	76%

*Binary circuits are built by shifters and adders to save hardware cost. The algorithm implemented by binary circuits are the 2nd Runge-Kutta method with 8-bit width. The stochastic circuits are also 8-bit width.

Stochastic vs. Binary Circuits with Different Bit Widths



Stochastic circuits with 10bit counters vs. 8-bit binary circuits

Advantages:

- **Energy per operation**
- Throughput per area
- □ Slightly better accuracy

Disadvantage:

□ Slightly longer runtime

EPO: Energy per operation TPA: Throughput per area

Comparison of stochastic and binary ODE solvers with different bit widths. For stochastic ODE solvers, it is the bit width of counter.

Conclusion and Future Work

- □ A novel design for solving an ODE is proposed by using a stochastic integrator to implement the accumulation in the Euler numerical method.
- □ The stochastic integrator provides unbiased estimate of the Euler numerical solution.
- □ The stochastic ODE solver has a lower energy consumption, higher TPA and shorter minimum runtime compared to binary designs.
- □ The error analysis shows that the sharing of RNGs is effective in reducing error for pseudorandom sequences, while it is less effective for LD sequences.
- Extended range of representation for the solutions will be investigated in the future work.

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Thank you for your attention.