ResNet-like Architecture with Low Hardware Requirements

Elena Limonova[1,2], Daniil Alfonso[3], Dmitry Nikolaev[2,4], Vladimir V. Arlazarov[1,2]

[1] FRC CSC RAS, Moscow, Russia
[2] Smart Engines Service LLC, Moscow, Russia
[3] JSC MCST, Moscow, Russia
[4] Institute for Information Transmission Problems RAS, Moscow, Russia

1. Motivation and Goal

There is a strong need for fast and efficient deep neural networks for modern recognition systems, especially for edge computing.
One way to do this is to use simplified bipolar morphological neuron model. The bipolar morphological neuron is based on the idea of replacing multiplication with addition and maximum operations. This model has been demonstrated for simple image classification with LeNet-like architectures.
In this work we introduce a relatively deep bipolar morphological ResNet (BM-ResNet) and analyze its efficiency and quality in image classification problems.

2. The BM neuron

The bipolar morphological neuron:

$$y_{BM}(\mathbf{x}, \mathbf{v}^+, \mathbf{v}^-, v_b) =$$

$$= \sigma\left(\sum_\alpha \sum_\beta p^\alpha p^\beta \exp \max_{j=1}^{N} (\ln x_j^\alpha + v_j^\beta) + v_b\right),$$

where $\alpha \in \{-,+\}$, $\beta \in \{-,+\}$, $p^+ = 1$, $p^- = -1$, N is an input length, $\mathbf{x}$ is an input vector, $\mathbf{v}^+$, $\mathbf{v}^-$ are weight vectors, v_b is a bias, and $\sigma(\cdot)$ is a non-linear activation,

$$x_j^+ = \begin{cases} x_j, x_j \geq 0, \\ 0, x_j < 0, \end{cases} \qquad x_j^- = \begin{cases} -x_j, x_j < 0, \\ 0, x_j \geq 0. \end{cases}$$

3. The BM convolutional layer

$I_{N\times M\times C}$ – input image
$J_{N\times M\times F}$ – output image
The standard convolutional layer:

$$J = \sigma(I * w + \mathbf{b}),$$

where $*$ is a convolution operation.
The BM convolutional layer:

$$J = \sigma\left(\sum_\alpha \sum_\beta p^\alpha p^\beta \exp(\ln I^\alpha \odot v^\beta) + \mathbf{b}\right),$$

where $\alpha \in \{-,+\}$, $\beta \in \{-,+\}$, $p^+ = 1$, $p^- = -1$, $\odot$ is a BM convolution operation:

$$(I \odot v)_{n,m,c} =$$

$$= \max_{c=1}^{C} \max_{\Delta n=0}^{K-1} \max_{\Delta m=0}^{K-1} I_{n+\Delta n, m+\Delta m, c} + v_{\Delta k, \Delta m, c, f}$$

4. BM network training

Conventional methods are not able to train a BM network from scratch, so we use an iterative approach:
1. Train standard network;
2. For each convolutional layer: replace layer with weights $\{w, b\}$ by the BM layer with weights $\{v^+, v^-, b\}$ and perform additional training using the same method as in step 1.

$$v_j^+ = \begin{cases} \ln|w_j|, \text{ if } w_j > 0 \\ -\infty, \text{ otherwise} \end{cases}$$

$$v_j^- = \begin{cases} \ln|w_j|, \text{ if } w_j < 0 \\ -\infty, \text{ otherwise.} \end{cases}$$

5. Hardware modelling

- Verilog HDL and Synopsys Design Compiler (65 nm)
- single-precision IEEE 754 addition, maximum, multiplication
- Approximations for exponent and logarithm;

Table 1: The estimate number of gates and latency for arithmetical operations

Op	Gates	Latency, clock cycles
add	16048	3
max	1464	2
mul	35345	4
log	154179	35
exp	256965	21

6. Convolutional layer complexity

Table 2: The gate number and latency ratios for standard and BM convolutional layers. Here F is filter number, C is channel number, $K \times K$ is filter size.

F	C	K	Gates, standard/BM	Latency, standard/BM
16	16	1	1.14	0.80
32	32	1	1.64	1.02
64	64	1	2.11	1.18
128	128	1	2.45	1.28
256	256	1	2.67	1,34
512	512	1	2.80	1.37
16	16	3	2.50	1.29
32	32	3	2.70	1.34
64	64	3	2.81	1.37
128	128	3	2.87	1.39
256	256	3	2.9	1.39
512	512	3	2.92	1.40

7. Experiments

We trained BM ResNet (see Fig. 1) for MNIST and CIFAR-10 classification problems.

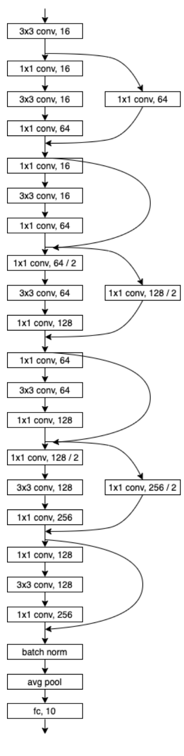

Figure 1: ResNet-22 architecture.

8. BM ResNet complexity

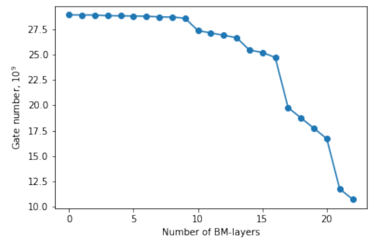

Figure 2: Gate number for convolutional layers of BM ResNet-22.

9. MNIST classification

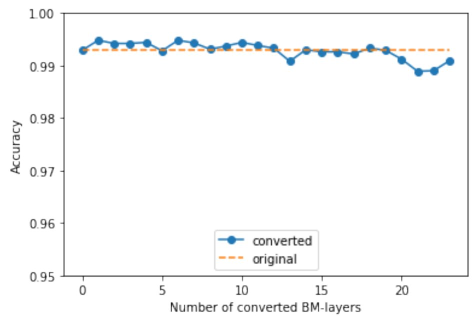

Figure 3: Accuracy after additional training on MNIST

ResNet: **99.3%**
BM ResNet: **99.1%**

10. CIFAR-10 classification

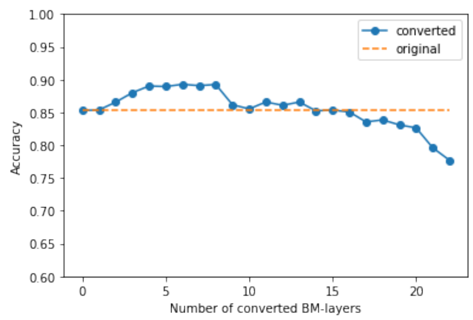

Figure 4: Accuracy after additional training on CIFAR-10

ResNet: **85.3%**
BM ResNet (16 BM layers): **83.9%**
BM ResNet (full): **77.7%**

11. Conclusion

1. We introduce BM ResNet architecture for image classification:
   - MNIST accuracy 99.1%
   - CIFAR-10 accuracy 83.9%
2. We present significant benefits of BM networks for ASIC: computationally intensive BM convolutions
   - require *2.1-2.9* less logic gates,
   - have *15-30%* lower latency.

Experimental code is available at https://github.com/SmartEngines/bipolar-morphological-resnet.