A Deep Learning System for Handwritten Digit Recognition

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EECE.7110 HPC-GPU Project - Midterm Presentation

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System Overview, Dataset

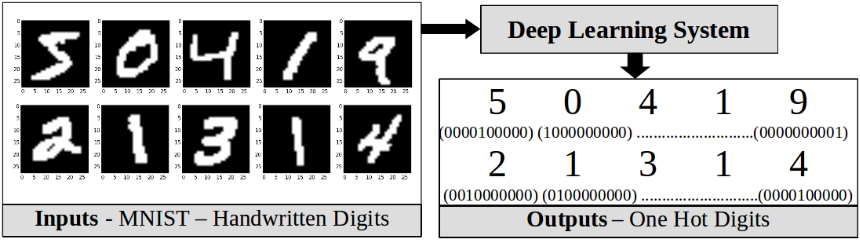


Figure 1: Overall System

- **Deep Learning System** - Based on a Convolutional Neural Network (CNN), implemented from scratch on CUDA
- **Goals** - Train the CNN to find digits in unseen test set images, achieve lower test error % than state-of-the-art - 0.23 [5]
- **Dataset** - MNIST [1] handwritten digits - 60000 train, 10000 test images, centered, scaled to 28×28 pixels, one-hot labels

Deep Learning System

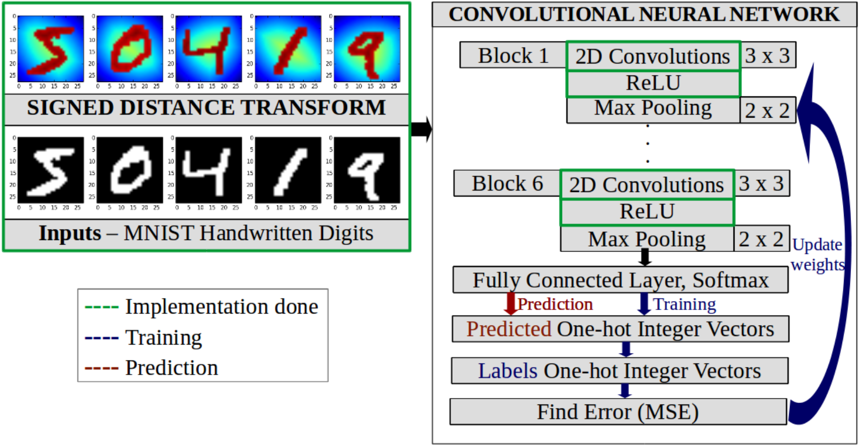
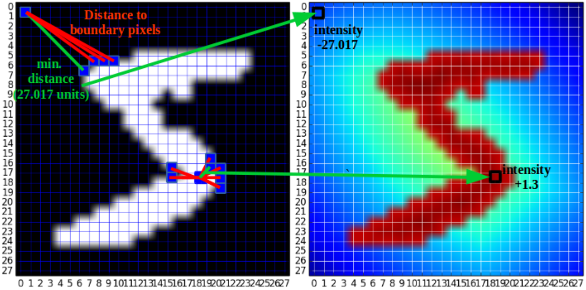


Figure 2: Deep Learning System

Signed Distance Transform Algorithm [2-4]

Algorithm 1 Signed Distance Transform

Inputs: Binary Images - Digit/Non-digit - **img**[n_{rows}][n_{cols}]
Outputs: Signed Distance Image **signedDist**[n_{rows}][n_{cols}]
for $i = 1$ to n_{rows} **do**
    for $j = 1$ to n_{cols} **do**
        $signedDist[i][j] = min(euclDist[x][y]) \forall (x, y) \ni I[x][y] = 1 - I[i][j]$
        $sign(signedDist[i][j]) =$ '+' if $I[i][j] = 1$ '-' if $I[i][j] = 0$
    end for
end for



Purpose:

-- Use as input to train and test the CNN

-- CNN learns to better distinguish the digit and non-digit pixels

--Could improve accuracy

Figure 3: Signed Distance Transform Algorithm

CUDA - Euclidean Distance

- to compute signed distances, we need euclDist between all pixel positions (denoted by i_n, j_n); calculated as

$$euclDist[i_1, j_1][i_2, j_2] = \sqrt{(i_2 - i_1)^2 + (j_2 - j_1)^2} \qquad (1)$$

- total number of operations required for this, $t = num_{rows} \times num_{cols} \times (num_{rows} \times num_{cols} - 1)/2$
- $num_{rows} = 28, num_{cols} = 28;\ t = 1 + 2 + \ldots + 784 = \frac{783 \times 784}{2}$
- $blockDim.x = 256, gridDim.x = 2$; each thread computes distances for 1 pixel

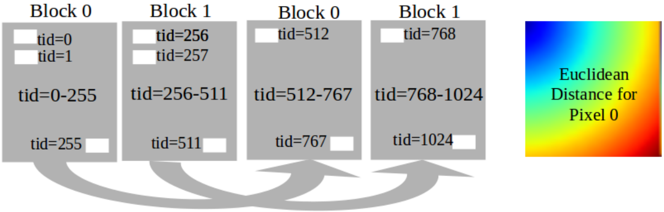


Figure 4: Euclidean Distance - CUDA Design

CUDA - Signed Distance Transform

- 60,000 train images; 784×784 operations for every image
- $blockDim.x = 784, gridDim.x = 1024$, shared $tmp\_dist[784]$
- each block deals with 1 pixel, each thread with 1 distance
- shared memory to store all boundary distances of current pixel
- find minimum distance using
  - parallel reduction
  - atomicMin() function - only supports int, convert float to int by $tmp\_dist \times 1000$, maintain this in a *signedDistInt* array
- use *__syncthreads*(), use thread 0 to assign the min to signedDist

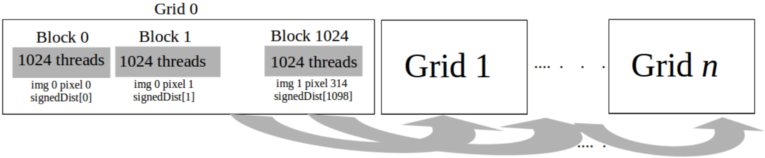


Figure 5: Euclidean Distance - CUDA Design

Signed Distance Transform - Outputs

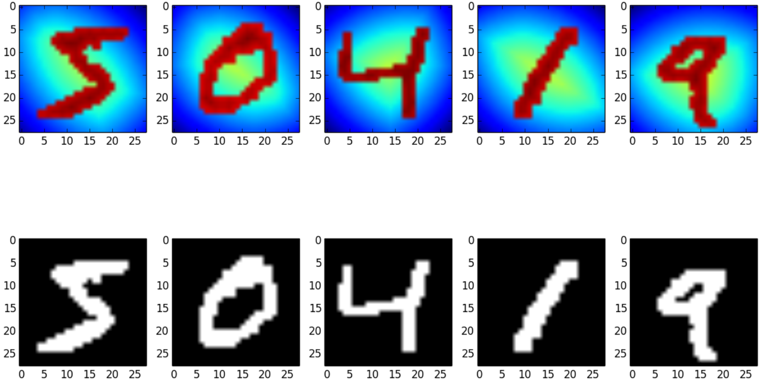


Figure 6: Euclidean Distance - CUDA Design

Convolution Operation

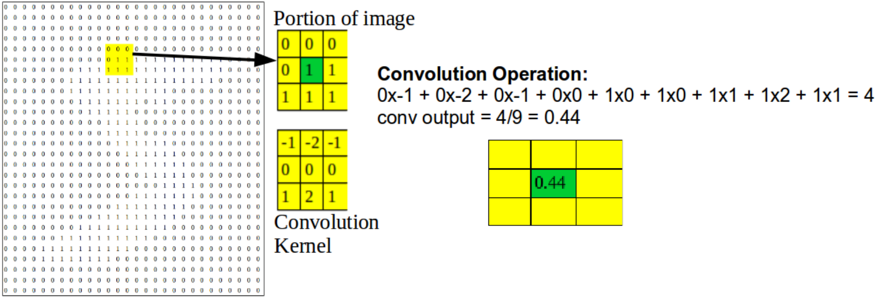


Figure 7: Convolution Operation

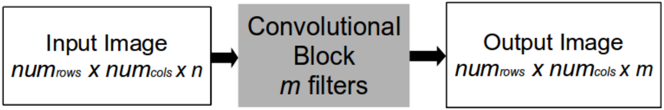


Figure 8: Convolution Layer

CUDA - Convolution Design

- a batch of train images (zero-padded), batch-size=32 -$32 \times 28 \times 28 \times 1$, kernel - 3×3
- total number of convolutions $t = 32 \times 28 \times 28$
- $blockDim.x = 1024$, $gridDim.x =$ batch-size=32
- each block deals with 1 image channel (784 convolutions)
- each thread performs one convolution
- *extern* shared memory - holds image channel of block
- the rows are repeatedly accessed for convolutions

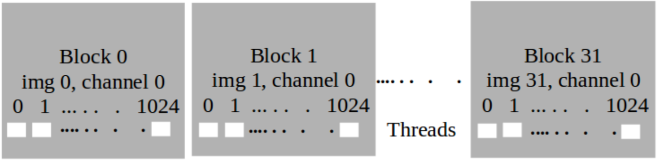


Figure 9: Convolution Layer

Convolution Sample Outputs

Using horizontal sobel edge detector [6-8] as weights (fixed)

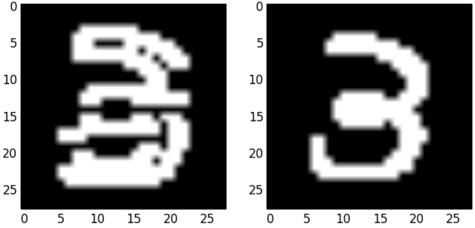


Figure 10: Convolved Output, Input Image

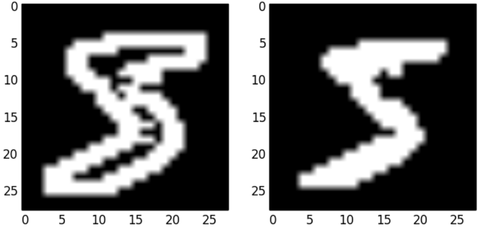


Figure 11: Convolved Output, Input Image

ReLU Layer, Performance

- activation function - to introduce non-linearity in the network
- applied to every pixel
- similar to a thresholding operation, defined as

$$ReLU(x) = max(0, x) \tag{2}$$

- not tested for now, will be tested after building the whole network
- CUDA implementation - same as convolutional blocks implementation

Task	Number of Operations	Time Taken
Euclidean Distance	$\frac{784 \times 783}{2}$	343 ms
Signed Distance (Parallel Reduction)	$60000 \times 784 \times 784$	229 ms
Signed Distance (Atomic Min)	$60000 \times 784 \times 784$	340 ms
Convolution, ReLU	32×784	$635us$

Table 1: Performance - Time Taken for Various Tasks Implemented

Progress

Tasks Completed:

- Signed Distance Transform
- Convolutional Layer
- ReLU Layer

Tasks Pending:

- Pooling Layer
- Fully Connected Layer
- Mean Squared Error Loss Function
- Gradient-based Training, Evaluation

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THANK YOU!