Image Classification from Coded Aperture

Jocelyn Ornelas Muñoz, Erica M. Rutter, Roummel F. Marcia

Department of Applied Mathematics, UC Merced
Imaging and Sensing Seminar

Monday, April 3, 2023

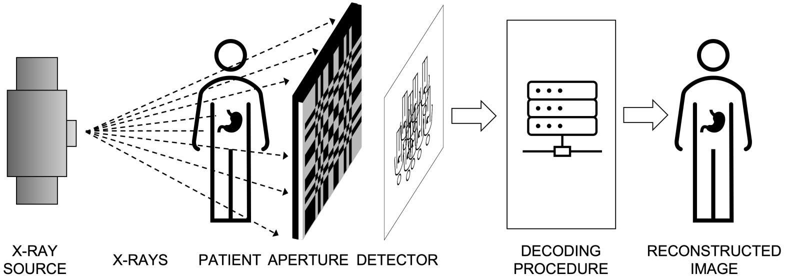
Motivation

In medical imaging, radiography typically uses apertures to modulate the radiation emitted by an x-ray source and produce high-resolution images.

Motivation

In medical imaging, radiography typically uses apertures to modulate the radiation emitted by an x-ray source and produce high-resolution images.

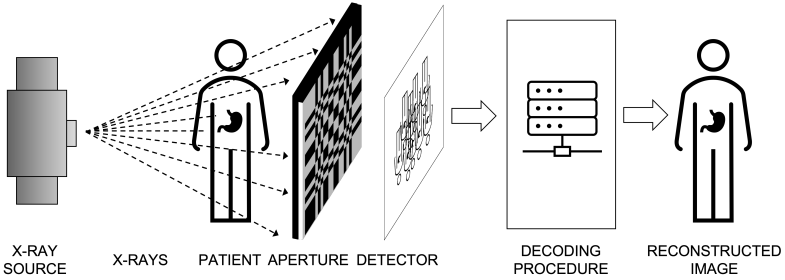
Problem: Complicated apertures require a decoding procedure to reconstruct the image.



Motivation

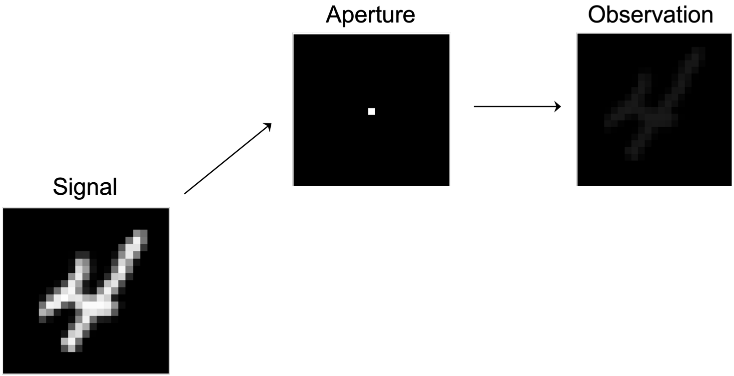
In medical imaging, radiography typically uses apertures to modulate the radiation emitted by an x-ray source and produce high-resolution images.

Problem: Complicated apertures require a decoding procedure to reconstruct the image.



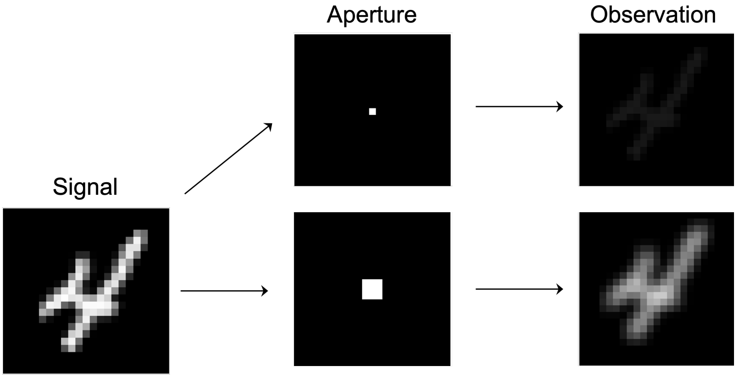
Goal: Classify images from coded observations without reconstructing the image.

Aperture Imaging



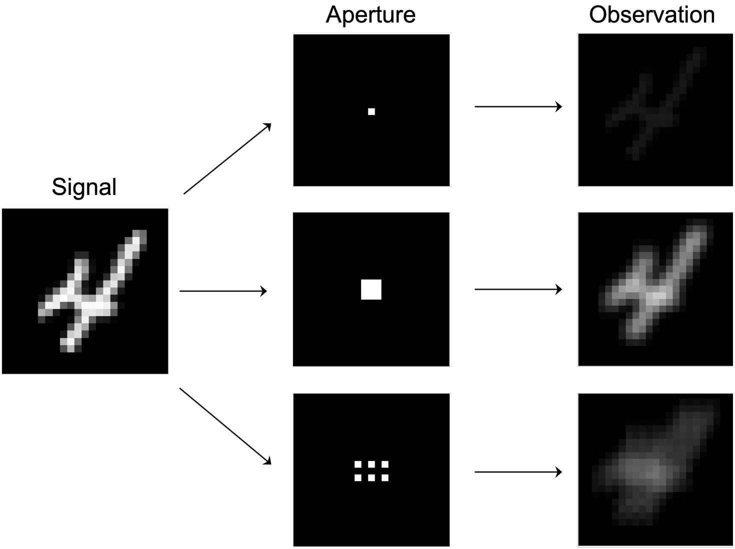
Small pinholes allow little light $\implies$ **faint** observatons

Aperture Imaging



Larger pinholes allow more light, but decrease resolution $\Longrightarrow$ **blurry** observations

Aperture Imaging



Multiple small pinholes $\Longrightarrow$ **overlapping** observations

Modified Uniformly Redundant Array (MURA)

A MURA pattern A consists of specified openings that has a corresponding decoding pattern G[1].

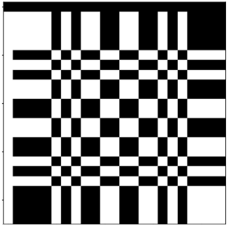
[1] Gottesman and Fenimore (1989)

Modified Uniformly Redundant Array (MURA)

A MURA pattern A consists of specified openings that has a corresponding decoding pattern G[1].

Let p be a prime number and $A = \{A_{ij}\}_{i,j=0}^{p-1}$ be the binary aperture array. Set

$$A_{ij} = \begin{cases} 0 & \text{if } i = 0 \\ 1 & \text{if } j = 0, i \neq 0 \\ 1 & \text{if } C_i C_j = +1 \\ 0 & \text{otherwise} \end{cases}$$



where

$$C_i = \begin{cases} +1 & \text{if } i \text{ is a quadratic residue modulo } p \\ -1 & \text{otherwise} \end{cases}$$

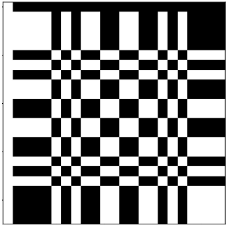
[1] Gottesman and Fenimore (1989)

Modified Uniformly Redundant Array (MURA)

A MURA pattern A consists of specified openings that has a corresponding decoding pattern G[1].

The decoding function G is constructed as follows:

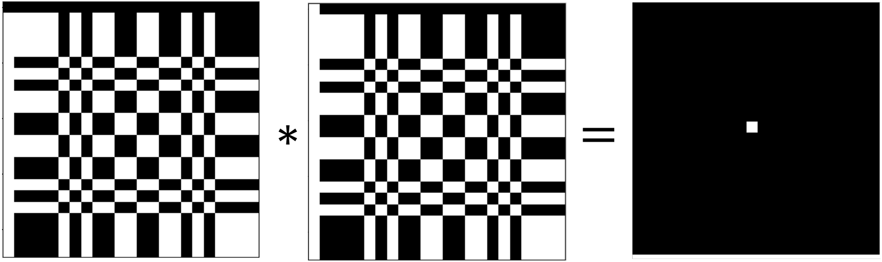
$$G_{ij} = \begin{cases} +1 & \text{if } i + j = 0 \\ +1 & \text{if } A_{ij} = 1, i + j \neq 0 \\ -1 & \text{if } A_{ij} = 1, i + j \neq 0 \end{cases}$$



[1] Gottesman and Fenimore (1989)

Modified Uniformly Redundant Array (MURA)

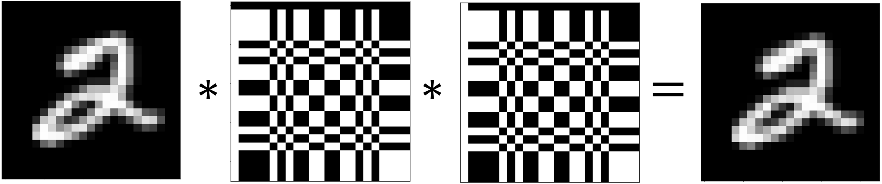
A MURA pattern A consists of specified openings that has a corresponding decoding pattern G[1].



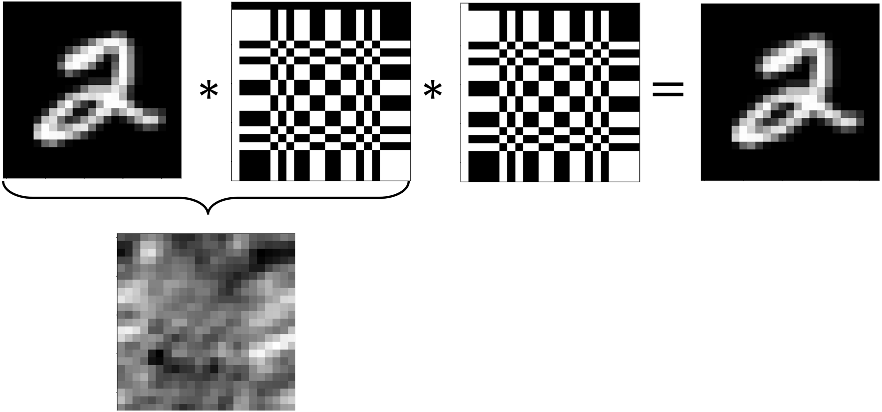
Coded aperture A Decoding pattern G δ

[1] Gottesman and Fenimore (1989)

Modified Uniformly Redundant Array (MURA)



Modified Uniformly Redundant Array (MURA)

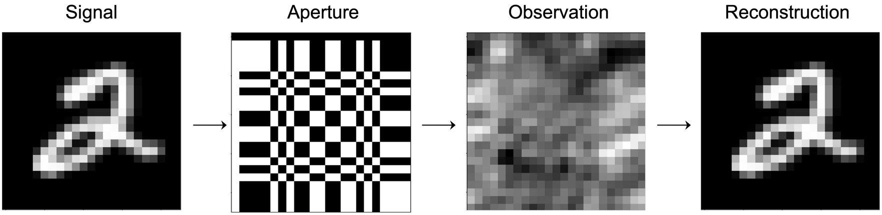


Coded observation

Coded observations appear irrecognizable, but MURAs are 50% open patterns[1] $\Longrightarrow$ decoded observations are much brighter than those from small pinhole cameras.

[1] Gottesman and Fenimore (1989)

MURA aperture imaging



S A D $\hat{S}$

The observation D is given by

$$D = S * A + B$$

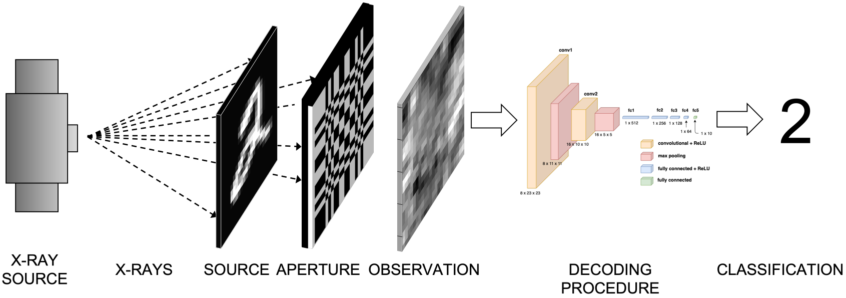
where B is background noise. The MURA reconstruction is given by

$$\hat{S} = D * G$$

where G is the decoding pattern.

Proposed Method

Goal: Classify handwritten digits from coded observations using a convolutional neural network (CNN) **without reconstructing the image**.



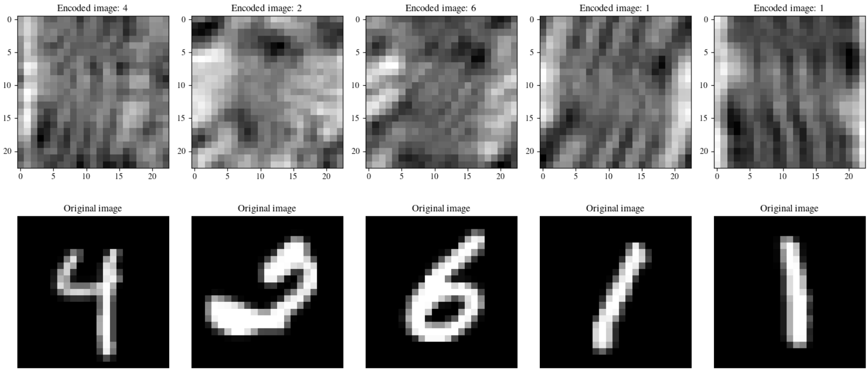
Experiment Set Up

Dataset: MNIST Handwritten Digits

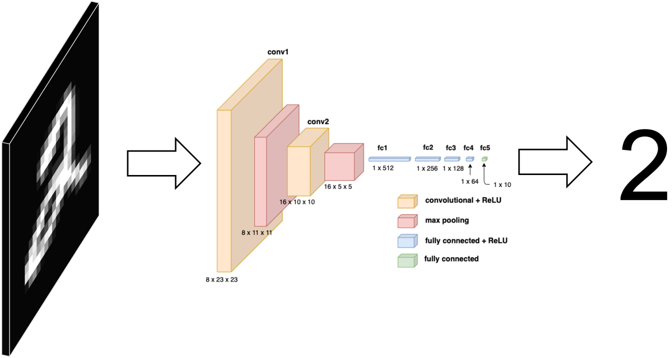
- 28×28 pixels (grayscale)
- $70,000$ total images
- 80% training, 10% validation, 10% testing images

Dataset: MNIST Handwritten Digits

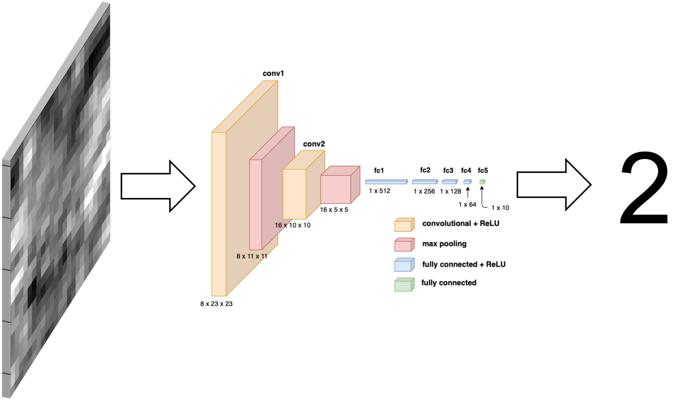
- 28×28 pixels (grayscale)
- $70,000$ total images
- 80% training, 10% validation, 10% testing images



Experiment 1: Classify original MNIST images

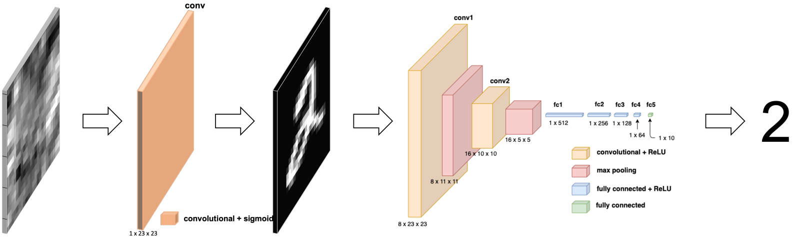


Experiment 1: Classify original MNIST images
Experiment 2: Classify encoded MNIST images



Experiments

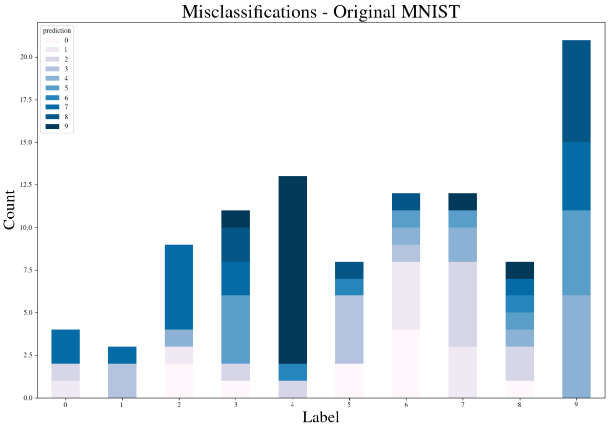
Experiment 1: Classify original MNIST images
Experiment 2: Classify encoded MNIST images
Experiment 3: Reconstruct encoded MNIST images, then classify from reconstructions



Classification accuracy of **original images**: 98.99%

Preliminary Results: Classification of original images

Classification accuracy of **original images**: 98.99%



The most common misclassified digits: $9, 4, 6, 7, 3$

Preliminary Results: Misclassification of original images

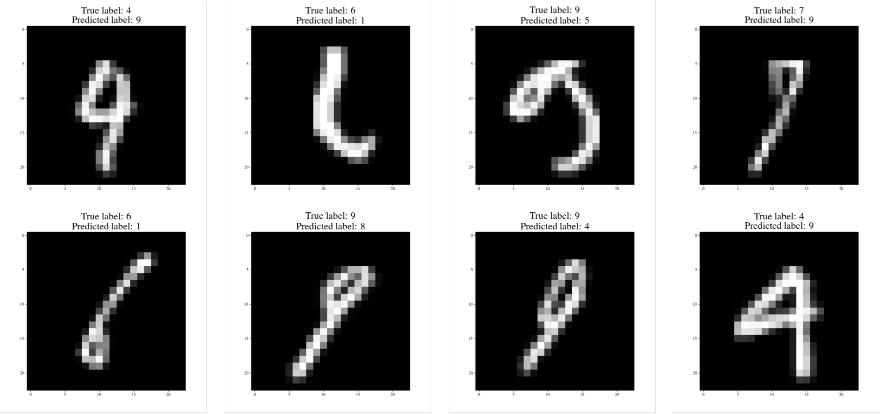


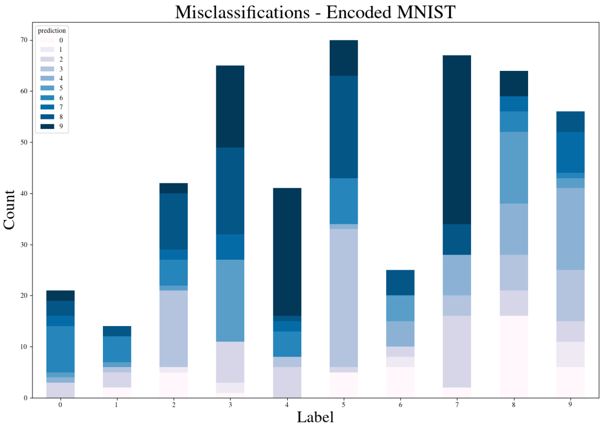
Figure 1: Examples of misclassified original MNIST images

Preliminary Results: Classification of encoded images

Classification accuracy of **encoded images**: 95.35%

Preliminary Results: Classification of encoded images

Classification accuracy of **encoded images**: 95.35%



The most common misclassified digits: $5, 7, 3, 8, 9$

Preliminary Results: Misclassification of encoded MNIST images

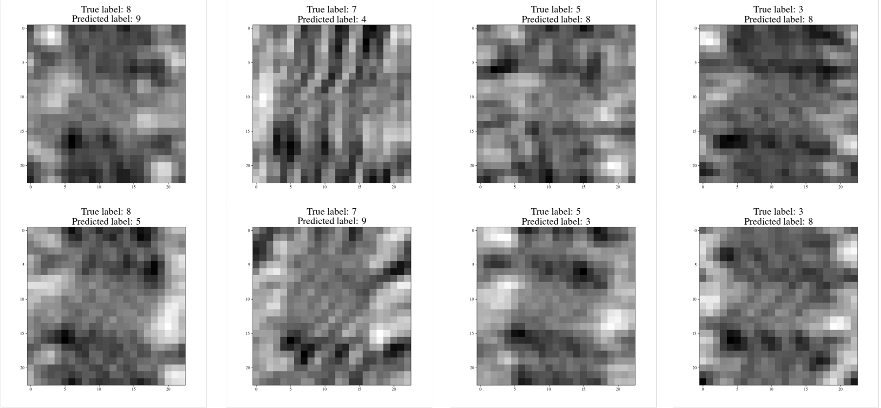


Figure 2: Examples of misclassified encoded images

Preliminary Results: Classification from reconstructed images

COMING SOON

Gracias!