Data augmentation of magnetograms for solar flare prediction

Allison Liu
Mentor: Dr. Wendy Carande
Motivation

Solar Research
We care to characterize and understand the Sun...it gives us life!

Protecting Astronauts
High-energy solar radiation is harmful to the human body and can cause biological damage

Space Exploration
Accurate solar flare prediction is a concern that inhibits space travel

Communications
Large solar flares can disrupt critical infrastructure like the power grid, GPS, and radio communications

Source: NASA
Source: NASA
Source: NASA
Source: NOAA
Introduction

Solar flare prediction is done largely by humans → Machine Learning ~2010

The goal:
Create a cohesive machine learning data set for solar flare prediction
We use line-of-sight magnetograms:

- from the SOHO/MDI magnetogram dataset (96m cadence)
- from the SDO/HMI magnetogram dataset (720s cadence)
**Methods: Image Translation**

Image-to-Image Translation: generate a synthetic version of an given image with a modification

Good for super-resolution problems!
Methods

Generative Adversarial Network (GAN) - 2014

Source Input Data → Real Target Data → Discriminator → Discriminator Loss

Source Input Data → Generated Target Data → Generator → Generator Loss

thiscatdoesnotexist.com
Generator Architecture
Model Exploration

Image Translation: Most models require INPUT→OUTPUT image training pairs

Pix2Pix (2016)
“General Purpose”
Paired

CycleGAN (2017)
Unpaired

CUT (2020)
Model training is faster and less memory-intensive
Unpaired

Isola et. al. 2016
Zhu et. al. 2017
Park et. al. 2020
**Results**

**Pix2Pix GAN**
- 200 epochs

**CycleGAN**
- 200 epochs

**CUT GAN**
- 400 epochs
Conclusion

Goal: Create a dataset of super-resolved SOHO/MDI images of SDO/HMI quality

- Identified data overlap
- Created image training pairs
- Tested 3 GAN models to upsample the MDI images
  - Pix2Pix introduced some strange image artifacts
  - CycleGAN and CUT worked well

- **Takeaways:**
  - Start simple
  - Modify existing and well-documented models
  - This technique shows promise for creating a high-quality combined solar magnetogram dataset!
Future Work

Next steps:

● Rotate MDI images in preprocessing
● Get a quantitative error calculation -- RMS Error
● Training, getting a new GPU!
  ○ More iterations
  ○ Training on full-sized images
  ○ Patchwise
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APPENDIX - CYCLEGAN

ature Image

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Patchwise contrastive learning

Feature extraction

$G_{enc}$

Encoder

$x$

$\hat{y}$

Park et. al. 2020
Discriminator Loss:

\[
H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot \log(p(y_i)) + (1 - y_i) \cdot \log(1 - p(y_i))
\]

GAN Loss:

\[
\mathcal{L}_{cGAN}(G, D) = \mathbb{E}_{x,y}[\log D(x, y)] + \mathbb{E}_{x,z}[\log(1 - D(x, G(x, z))],
\]

\[
\mathcal{L}_{L1}(G) = \mathbb{E}_{x,y,z}[\|y - G(x, z)\|_1].
\]

\[
G^* = \arg \min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G).
\]

Isola et. al. 2016