Enhancing Resolution of Solar Magnetograms: A Latent Diffusion Model Approach

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Goal of the project

Machine Learning Goal

Create a deep learning algorithm to perform a x4 spatial super-resolution (SR) and compare it with existing techniques.

Why do we want to do this analysis?

Apply the SR algorithm to MDI images and increase their spatial resolution from 2"/pixel to 0.5"/pixel matching the HMI resolution.

1. The dataset
2. Model choice and setup
3. Results

Data sources

- Data from HMI/SDO and MDI/SOHO instruments; simultaneous operation from May 2010 to April 2011 yielded 4126 data pairs,
- Downscaling HMI images ($4096 \times 4096 \rightarrow 1024 \times 1024$) (2013–2019) achieves MDI-equivalent 2"/pixel resolution, resulting in 43,912 paired images,
- Image values constrained to $\pm$ 3000 G and normalized to a range of -1 to 1,

1 The dataset

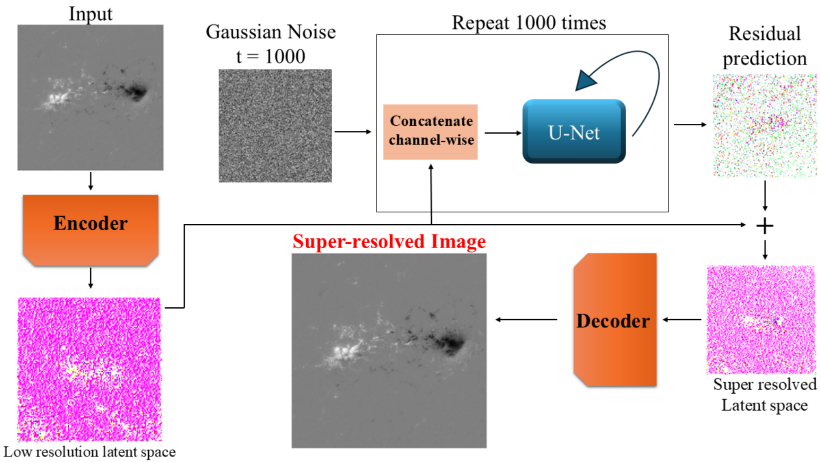
2 Model choice and setup

3 Results

Key points

- Train on HMI-data only where we create a MDI-equivalent 2''/pixel resolution image by averaging every 4 pixels of the HMI data,
- Finetune with the LoRA technique on the MDI/HMI paired dataset from May 2010 to April 2011
- After evaluation use the Fourier analysis to determine which model is really predicting features smaller than 2"/pixel.

Inference algorithm



1 The dataset

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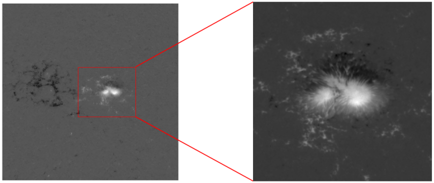
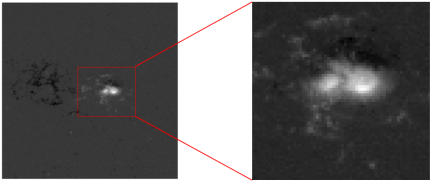
Input and Target



(a) Ground Truth

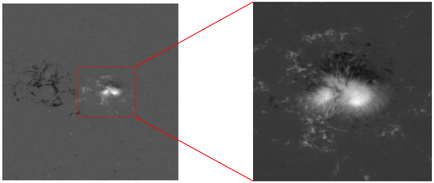


(b) Input

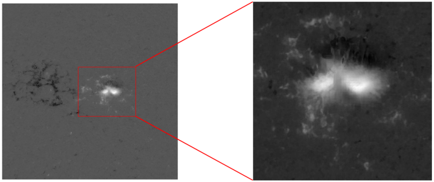
Table Results

Metric	LDM RES (Ours)	Enhance (Díaz Baso & Asensio Ramos 2018)	Progressive (Rahman et al. 2020)
PSNR ↑	29.23 ± 8	**30.02 ± 9**	29.71 ± 8
SSIM	0.8 ± 0.05	**0.9 ± 0.03**	0.8 ± 0.04
LPIPS ↓	**0.08 ± 0.03**	0.16 ± 0.04	0.16 ± 0.04
FID ↓	**0.04 ± 0.01**	0.7 ± 0.2	2.3 ± 0.3
Unsigned Magnetic Flux (%)	**18 ± 13**	27.5 ± 26.7	28.5 ± 15.0
AR Size (%)	**25 ± 18**	35 ± 69	36 ± 38

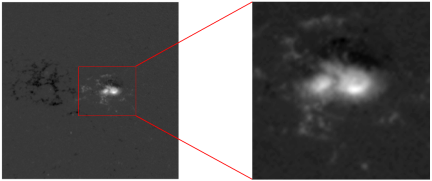
Visual Inspection



(a) Ground Truth

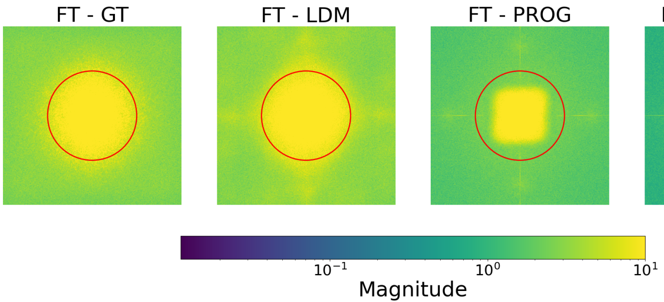


(b) Best LDM model

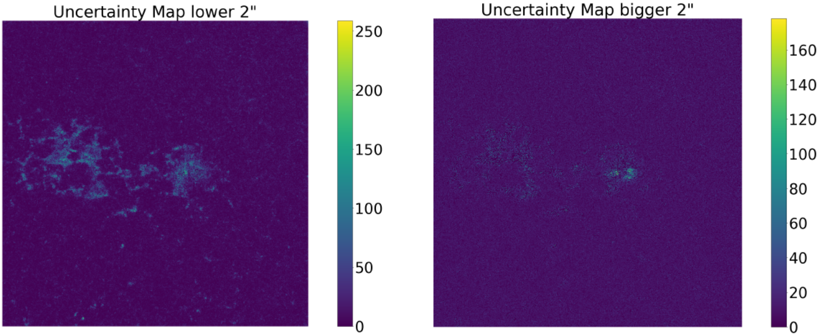


(c) Best classic model

Fourier Analysis



Fourier Analysis



Summary

- We propose a novel method based on Latent Diffusion Models (LDM) to achieve super-resolution for solar magnetograms, enhancing MDI data from 2"/pixel to match HMI's 0.5"/pixel resolution,
- Our LDM approach outperforms deterministic models (e.g., Enhance and Progressive) in perceptual metrics like LPIPS and FID, demonstrating better detail preservation and generalizability with minimal fine-tuning on MDI/HMI pairs.
- The stochastic nature of LDM allows the generation of uncertainty maps, highlighting prediction challenges, and enabling reliable super-resolution of features smaller than 2", while maintaining larger-scale features.

What are the DDPMs?

Diffusion Probabilistic models are very popular nowadays and we can summarize their usage into the following bullet points:

- Forward process or noising process (Ho et al., 2020):

$$q(x_{1:T}|x_0) = \prod_{t=1}^{T} q(x_t|x_{t-1}),\ q(x_t|x_{t-1}) = \mathcal{N}(x_t; \sqrt{1-\beta_t}x_{t-1}, \beta_t\mathcal{I}) \tag{1}$$

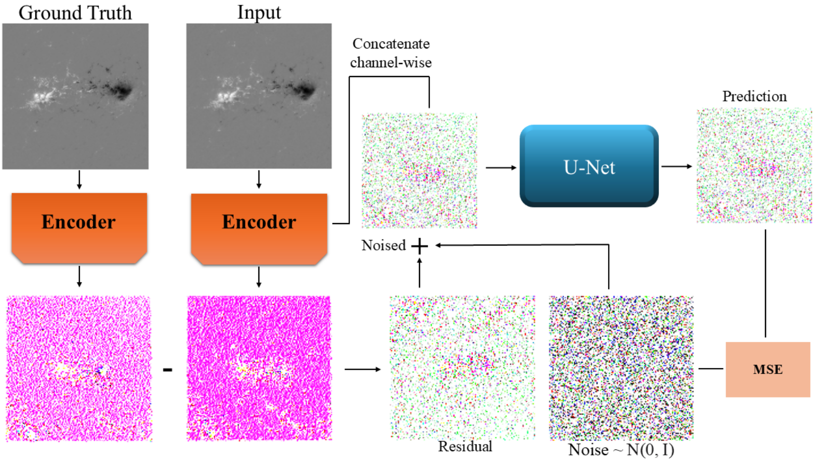
- Reverse process or denoising (Ho et al., 2020):

$$p_\theta(x_{t-1}|x_t) := \mathcal{N}(x_{t-1}; \mu_\theta(x_t, t), \Sigma_\theta(x_t, t)) \tag{2}$$

Palette-like approach

- To apply the Denoising Diffusion Probabilistic Models for Image-to-Image translation we applied the Palette approach (Chitwan Saharia et al 2021),
- Given a set of paired data (x_i, y_i), where:
  1. x_i: input image,
  2. y_i: target image,
- Training step: we noise the target image with a random number of timesteps t, we concatenate the target image and the input image channel-wise, pass through the model and we predict the noise that we added on the target image.

Training algorithm



Metrics

- FID:
  1. $FID(x, g) = ||\mu_x - \mu_g||^2 + \mathrm{Tr}(\Sigma_x + \Sigma_g - 2(\Sigma_x \Sigma_g)^{(1/2)})$,
- PSNR:
  1. $\mathsf{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathsf{MAX}^2}{\mathsf{MSE}}\right)$
- SSIM:
  1. $\mathsf{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$
- LPIPS: L2 Norm in a VGG latent space.