Generation of magnetograms using image-to-image translation on EUV images

Vincent Barra[(1)], Véronique Delouille[(2)]

(1) Clermont Auvergne University, CNRS, LIMOS

(2) STCE/Royal Observatory of Belgium

Objective

- Direct access to magnetograms from a limited number of sources recordings.
- EUV images offer vantage points from the far side of Sun.

Objective: Generate magnetograms out of EUV images, and assess the errors made when using the generated models into PFSS

Image to Image translation

- Learn an input/output mapping.
- Unsupervised/supervised methods.
- Paired / unpaired translations.
- Applications: collection style transfer, object transfiguration,season transfer, photo enhancement....

Dataset

Dataset of AIA and HMI specifically prepared for helping machine learning operations [1].

- rebinned on 1024×1024 images.
- 2 min cadenced.
- spatially and temporally aligned.

2010-2012 images shuffled into training/test set.

Dataset	#
Training set	12 000
Test Set	3 945

Implementation

- Model trained on an Intel Xeon Gold 2.11 GHz, 4 NVIDIA Titan XP GPUs.
- Implementation issues: Python 3.5, Tensorflow 1.14.
- Algorithm parameters: Adam optimizer, learning rate $=10^{-4}$.
- Training time: 4 days.

Validation

- Visual assessment (difference map in log scale on the test set).
- Quantitative indexes: MSE, cross-partial correlations
- Physical error: using the generated models into PFSS models.

Perspectives

- Input of models of the solar wind
- Train on more images / years.
- Explore other channels / multichannels image translation.
- Fuse information from different channels to generate magnetograms.

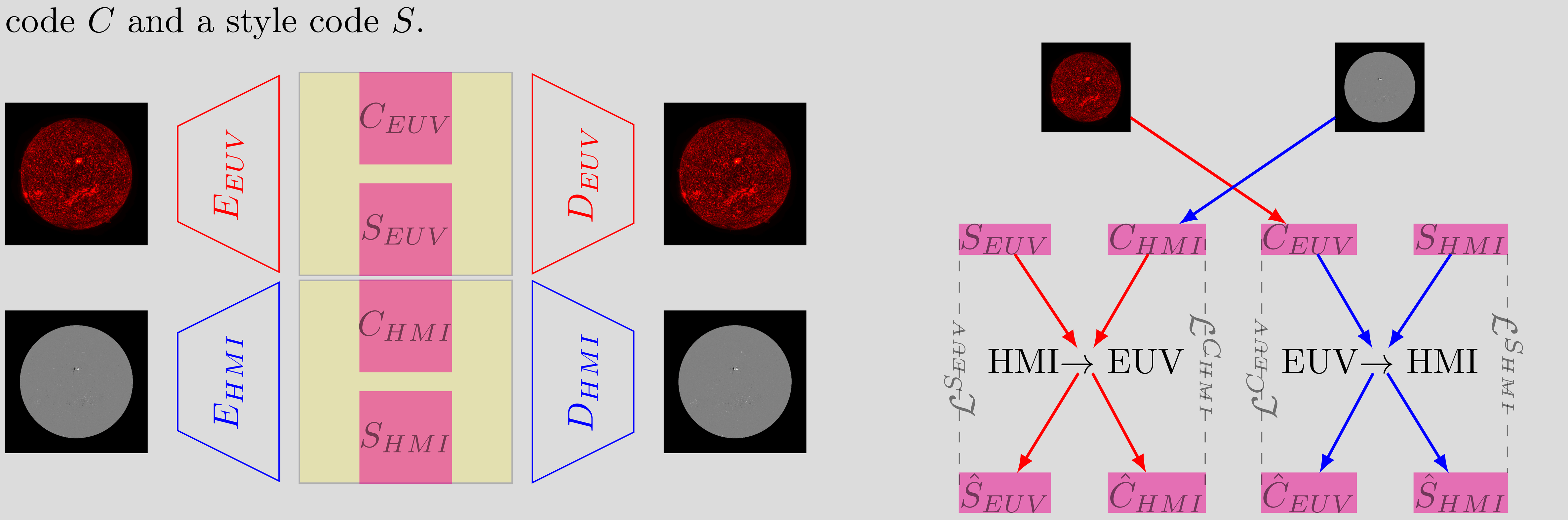
Algorithm

Adaptation of a multimodal Image to Image translation algorithm [2].

- The latent space of images can be decomposed into a content space C and a style space S
- Images in the domains share a common C, but not the S's.
- Image translation is performed by combining its content code with the style code of an image in the target space (paired or unpaired).
- Using random target styles, it is possible to provide several realizations of the translation.

Content and Style encoding

For each domain (EUV,HMI), the latent space of autoencoders (E, D) is factorized into a content code C and a style code S.



Losses

- Bidirectional loss: $\forall x \in \{EUV, HMI\}$ $\quad \mathcal{L}^x = \mathbb{E}_{x\sim p(x)}\left[\|D_x(C_x, S_x) - x\|_1\right]$
- Latent reconstruction: with $q \sim \mathcal{N}(0,1)$ and $x \neq y \in \{HMI, EUV\}$:
  - $\mathcal{L}^{C_y} = \mathbb{E}_{C_y\sim p(C_y), S_x\sim q(S_x)}\left[\|C_x(D_x(C_y, S_x) - C_y\|_1\right]$
  - $\mathcal{L}^{S_x} = \mathbb{E}_{C_y\sim p(C_y), S_x\sim q(S_x)}\left[\|S_x(D_x(C_y, S_x) - S_x\|_1\right]$
- Adversarial losses: if G_x is a discriminator trying to distinguish between real and fake x images,

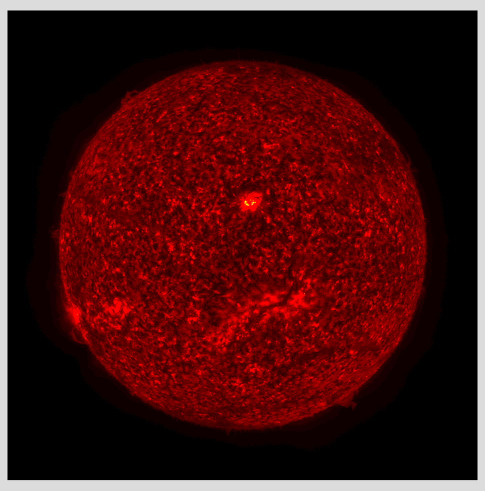
$$\forall x \neq y \in \{HMI, EUV\} \mathcal{L}^x_G = \mathbb{E}_{C_y\sim p(C_y), S_x\sim q(S_x)}\left[log(1 - G_x(D_x(C_y, S_x))) + \mathbb{E}_{x\sim p(x)} log(G_x(x)\right]$$

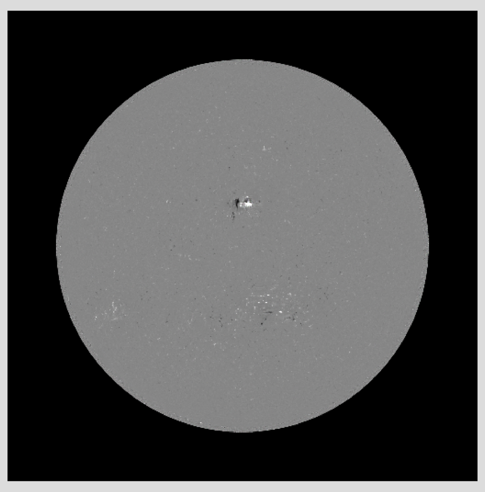
Total Loss: if x=HMI, y=EUV

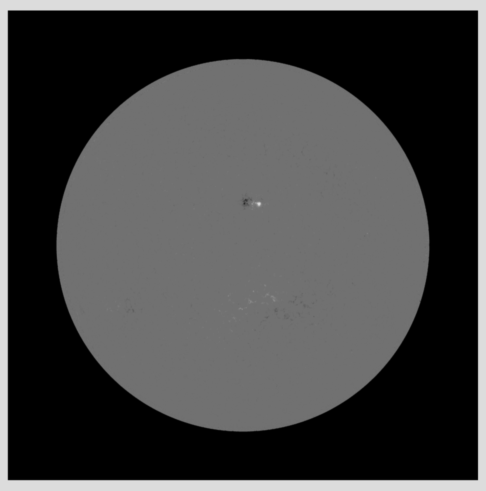
$$\min_{\mathbf{E_x E_y D_x D_y}} \max_{\mathbf{G_x G_y}} \mathcal{L}^{\mathbf{x}}_{\mathbf{G}} + \mathcal{L}^{\mathbf{y}}_{\mathbf{G}} + \lambda_1(\mathcal{L}^{\mathbf{x}} + \mathcal{L}^{\mathbf{y}}) + \lambda_2(\mathcal{L}^{\mathbf{C_x}} + \mathcal{L}^{\mathbf{C_y}}) + \lambda_3(\mathcal{L}^{\mathbf{S_x}} + \mathcal{L}^{\mathbf{S_y}})$$

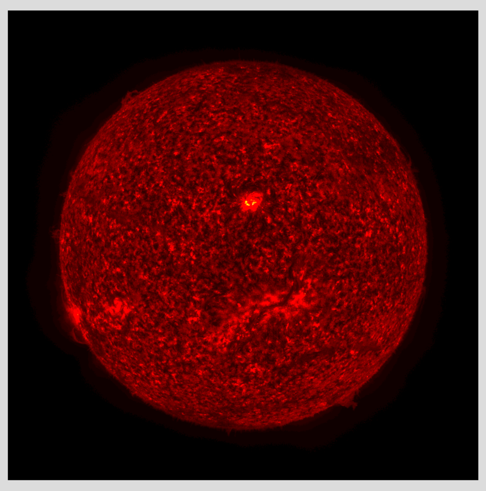
Results

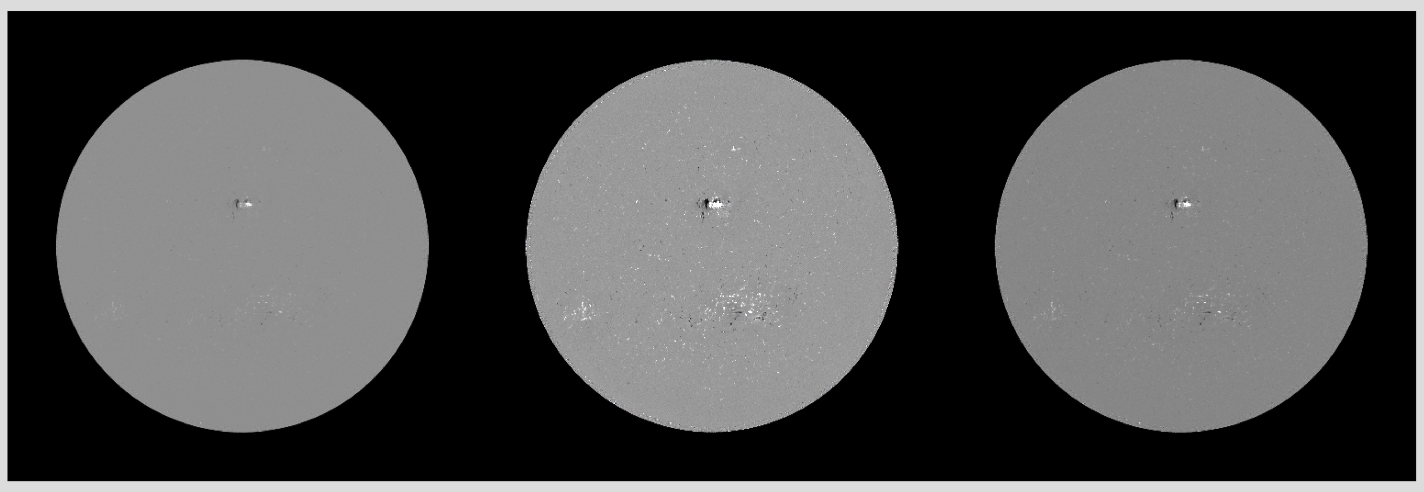
Example: images taken on May, 23^{rd} 2010

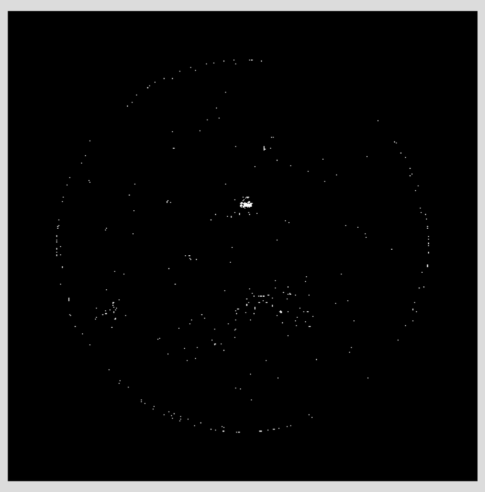

304 EUV image


Translation in HMI Bz


HMI Bz image


Translation in 304 EUV.


Different translation styles (304→ HMI translation)


HMI Translation Error (log scale)

References

[1] R. Galvez et al. A machine learning dataset prepared from the nasa solar dynamics observatory mission. *The Astrophysical Journal Supplement*, 242(1), 2019.

[2] Xun Huang et al. Multimodal unsupervised image-to-image translation. In *ECCV Munich, September 8-14, 2018, Proceedings, Part III*, pages 179–196, 2018.