ITI for the Sun:

Improved intercalibration of multi-instrument heliophysics data series

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Abstract: In solar physics, the study of long-term evolution typically exceeds the lifetime of single instruments. Data-driven approaches are limited in terms of homogeneous historical data samples. We demonstrate how machine learning enabled Instrument-To-Instrument translation (ITI; Jarolim et al. 2022) can leverage recent instrumental improvements and provide a so far unused resource to foster novel research and accelerate data-driven solar research. In this study, we aim at providing a uniform data series of EUV observations from SDO/AIA, STEREO/EUVI and SOHO/EIT. The application of unpaired image-to-image translation methods to standard reduced SDO/AIA data shows a sensitivity for insufficiently corrected device degradation, leading to differences between the calibrated series. Here, we apply the auto-calibration from Dos Santos et al. (2021), to obtain a more consistent calibration for the SDO/AIA series and use the ITI framework to translate observations from STEREO/EUVI and SOHO/EIT to the same domain. We demonstrate that with this adjustment we can achieve an accurate calibration between the three instruments. Comparisons of aligned observations demonstrate high perceptual quality and a strong similarity to reference observations. The resulting data series covers uniform observations dating back to 1996, including simultaneous observations from multiple vantage points. This method paves the way towards a new generation of solar cycle studies of the solar EUV corona, contributes additional samples for data-driven methods and enables the application of automated methods that were developed specifically for SDO/AIA data to the full EUV data series without further adjustments.

Introduction

We provide a general method that translates from a given low-quality domain to a target high-quality domain (Instrument-To-Instrument translation; ITI). We overcome the limitation of a high-quality reference image with the use of unpaired image-to-image translation (Zhu et al. 2017), where we use real observations from state-of-the-art instruments in observational solar physics, to model the image distribution of high-quality images. With this approach, we infer information from real observations to enhance physically relevant features which are otherwise beyond the diffraction limit of the telescope (e.g., super resolution), inter-calibrate data sets and estimate observables that are not covered by the instrument. In this study, we aim to translate between the instrumental characteristics of SDO, STEREO and SOHO (EUV).

Device degradations limit a consistent translation between observation series and correction methods show differences.

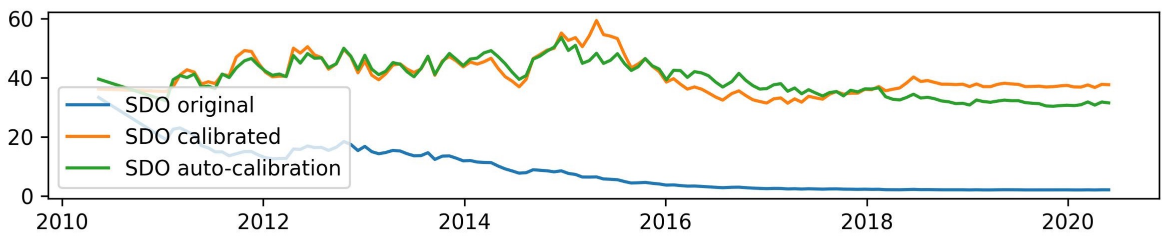


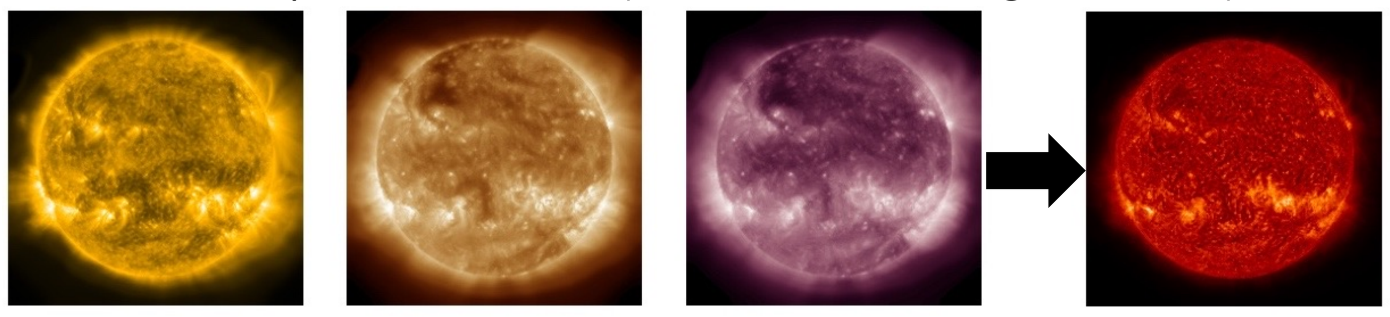
Figure 1: 304 Å mean intensity and correction of degradation

SDOML - ITI translation playground

SPACEML

The ITI translation is designed as general framework for performing image translations of solar observations. We use the machine learning ready data set of SDO observations (SDOML; Galvez et al. 2019), to provide example applications of ITI. The SDOML dataset covers observations from 2010 to 2018 and is publicly available in the NumPy compressed array format (npz).

We provide a Colab notebook for model training of two applications. 1) Reconstruction of the chromospheric 304 Å channel based on coronal EUV observations (171, 193, 211 Å; result image below). 2) Estimation of the line-of-sight magnetogram (SDO/HMI) based on the EUV filtergrams. The notebook is publicly available and allows the use of online computational resources to experiment with ITI (QR-code; the link is given below).



ITI Method

Our primary model architecture consists of two neural networks, where the first generates synthetic low-quality images from a given high-quality image (*generator BA*). The second network is trained to invert the image degradation to reconstruct the original high-quality observation (*generator AB*). We enforce the generation of low-quality images with the use of competitive training between generator BA and a discriminator network. We include an additional noise factor for generator BA to model a variety of degrading effects, independent of the image content. With the synthesis of more realistic and diverse low-quality observations, the generator AB is capable of providing a similar reconstruction performance for real low-quality observations. The artificial degradation leads inevitably to an information loss that needs to be compensated by the generator AB to reconstruct the original image. Analogously, we enforce that images by generator AB correspond to the domain of high-quality images, restricting the possible enhanced solutions and gaining information from the high-quality image distribution.

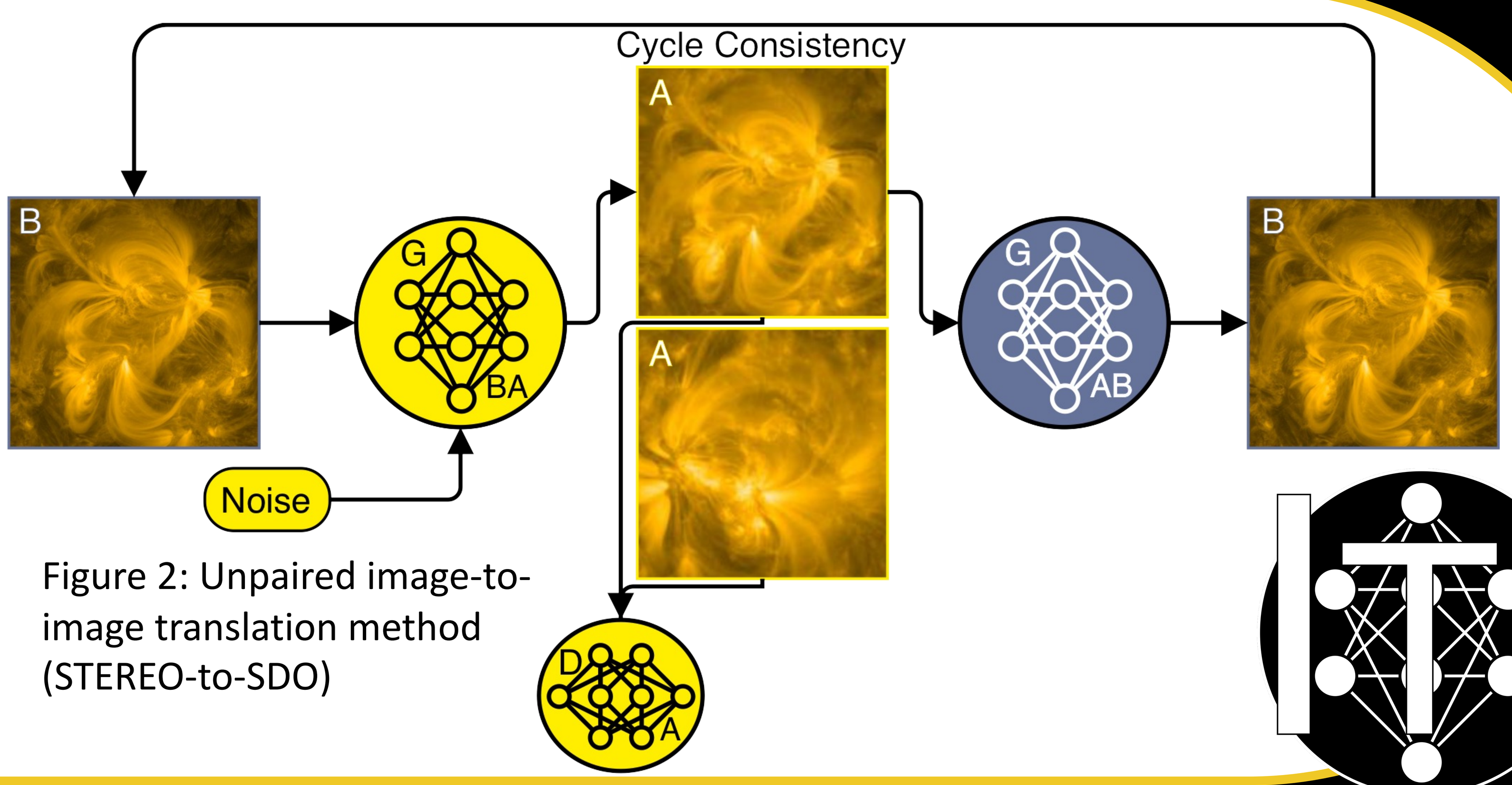
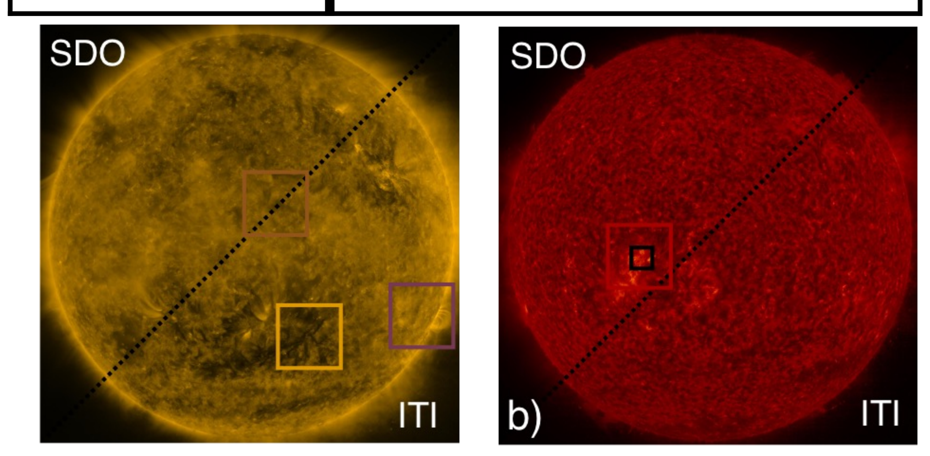


Figure 2: Unpaired image-to-image translation method (STEREO-to-SDO)

Results - Direct comparison of aligned observations

We apply our method to the full data sets where we use a strict temporal separation between train and test set. For 2010, simultaneous observations from SDO and SOHO allow for a direct comparison. In Fig. 3 a perceptual quality increase and strong similarity to the reference can be observed in the results. For a statistical evaluation of the perceptual quality, we use the FID, which shows that ITI enhanced observations are closer to the high-quality image distribution. The intercalibration of the data series results from this feature dependent enhancement.

Instruments	Fréchet Inception Distance (FID)	
	low-quality	ITI
SOHO to SDO	27.62	6.32
STEREO to SDO	23.30	13.3



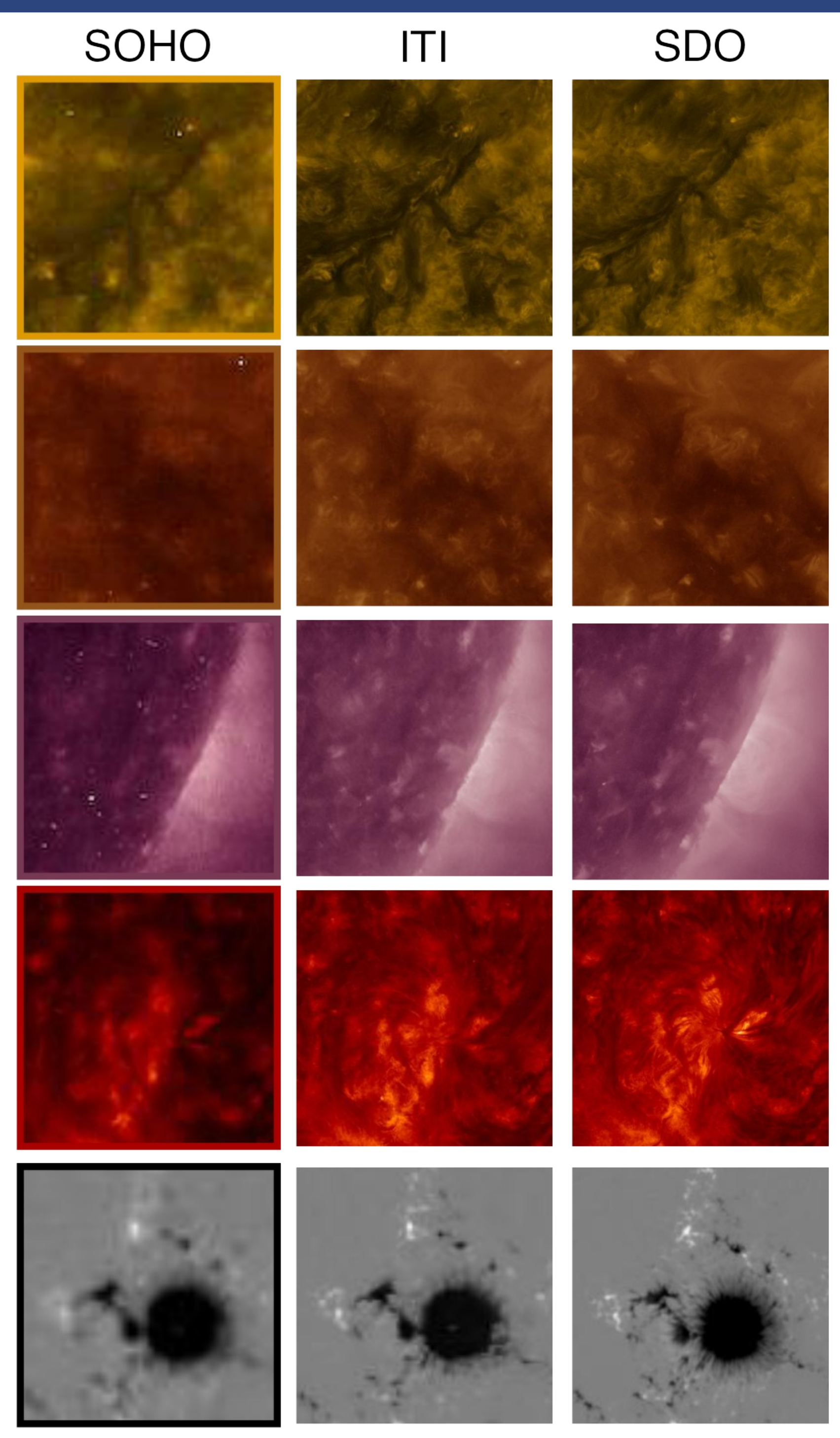


Figure 3: Comparison of ITI enhanced observations

Results - Intercalibration

We found that device degradations are not automatically adjusted by ITI, which makes a prior correction inevitable. For the SDO reference we use the SDO auto-calibration, for SOHO the *eit_prep* routine, and for STEREO we apply a first-order correction for the 304 Å channel. As independent baseline for intercalibration we fit the mean and std based on quiet-Sun regions. Figure 4 shows the smoothed mean intensities over the full data set and the table below summarizes the mean absolute error of temporally aligned observations. The baseline calibration fails for the solar maximum, while ITI provides a more consistent timeseries. The small deviation from simultaneous observations suggest also valid calibrations for pre-SDO times.

	Original	Baseline	ITI
MAE - STEREO	128.1	17.4	10.7
MAE - SOHO	45.4	5.4	6.6

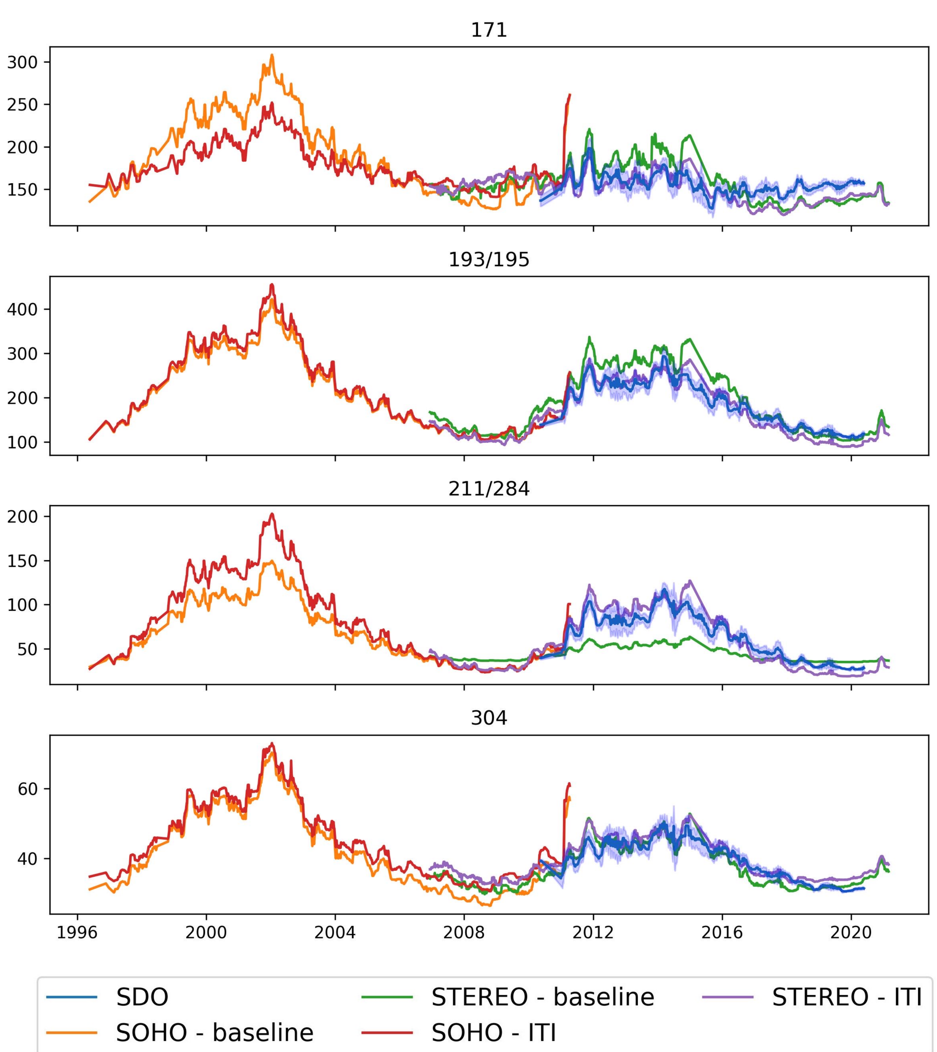


Figure 4: Evaluation of the calibrated timeseries

Conclusion

Recent AI methods for calibration and translation provide a high confidence intercalibration. We demonstrate that ITI learns the key characteristics of high-quality observations, enabling an informed image enhancement. The resulting unified series of space-based EUV observations enables the integrated use of the three satellite missions from very different vantage points and demonstrates ITI as a tool for enhanced data fusion products.

References

- Dos Santos, Luiz FG, et al. "Multichannel autocalibration for the Atmospheric Imaging Assembly using machine learning." Astronomy & Astrophysics 648 (2021): A53.
- Zhu, Jun-Yan, et al. "Unpaired image-to-image translation using cycle-consistent adversarial networks." Proceedings of the IEEE international conference on computer vision. 2017.
- Galvez, Richard, et al. "A machine-learning data set prepared from the NASA solar dynamics observatory mission." The Astrophysical Journal Supplement Series 242.1 (2019): 7.
- Jarolim, Robert, et al. "Instrument-To-Instrument translation: Instrumental advances drive restoration of solar observation series via deep learning." (2022).

Code availability: https://github.com/RobertJaro/InstrumentToInstrument

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