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Application of Deep Learning to Solar and Space Science Data

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In this talk, we introduce our recent applications of deep learning to solar and space science data. Our major applications are (1) generation of solar farside magnetograms[1] and global field extrapolation, (2) generation of solar UV/EUV images[2], (3) denoising solar magnetograms[3], (4) generation of modern satellite images from Galileo sunspot drawings, (5) improvement of global IRI TEC maps[4], (6) one-day forecasting of global TEC maps, (7) generation of high-resolution magnetograms from Ca II K images[5], (8) generation of super-resolution magnetograms[6], (9) flare classification[7] and visual explanation[8], and (10) forecasting solar X-ray profiles[9].

(1) We successfully generate farside solar magnetograms from STEREO/EUVI images using a deep learning model (pix2pix[10]) for image translation method. For this, we train the model using pairs of SDO/AIA images and SDO/HMI magnetograms, then apply to the STEREO/EUVI images. Figure 1 shows a series of 304-Å images and magnetograms, which makes it possible to monitor the temporal evolution of this active region from the farside to the frontside of the Sun when farside EUV data are available. Our global field extrapolation based on AI-generated data are more consistent with observations than before in view of active regions and coronal holes.

(2) We successfully generate solar UV/EUV images from solar magnetograms using a couple of deep learning methods.

(3) We successfully denoise solar magnetograms using a deep learning method for image translation by training pairs of SDO/HMI magnetograms and 21-frame-stacked magnetograms. Noise levels of the denoised magnetograms are greatly reduced.

(4) We successfully generate modern satellite data (solar magnetograms and EUV images) from Galileo sunspot drawings using a deep learning model. Unsigned magnetic fluxes and EUV intensities obtained from the AI-generated data are approximately consistent with real ones.

(5) In this work, we have successfully made an improvement of IRI global TEC maps by a deep learning model. AI-generated TEC maps are much more consistent with the corresponding IGS TEC maps than the IRI ones.

(6) We have successfully made a one-day forecasting model of global TEC maps by using a deep learning method. For training, we use two sets of input data: the present-day global TEC map and one-day difference map. Our model well generates TEC values over equatorial anomaly regions and is better than the previous models.

(7) We successfully generate high-resolution magnetograms from Ca II K images using an improved image translation model (pix2pixHD[11]).

(8) We have successfully applied two novel deep learning methods to enhance the resolution of SDO/HMI magnetograms. Our methods are better than conventional bicubic methods.

(9) We have successfully developed three flare forecast models based on novel deep learning methods (CNN) using only full-disk magnetograms. Our models are better than the previous models in view of statistical scores. Visual explanation methods for a deep learning flare classification model show that our model considers the vicinity of polarity inversion lines more important than the rest area of active regions.

(10) We successfully forecast solar X-ray profiles using novel deep learning methods (seq2seq with LSTM and attention). Our methods are much better than conventional regression methods.

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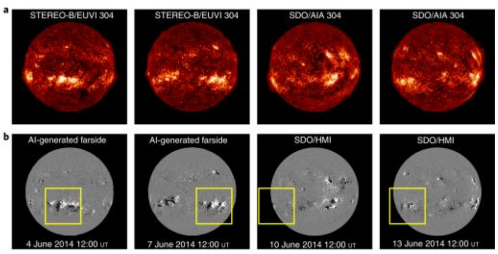

Figure 1. A series of 304-Å images and magnetograms. a: The first two 304-Å images are taken from STEREO-B/EUVI and the last two from SDO/AIA. b: The first two magnetograms are AI-generated farside ones from the model and the last two are taken from SDO/HMI. The yellow boxes show the tracking of the NOAA active region 12087 from the farside to the frontside.