Magnetic field extrapolations constrained by the coronal loops

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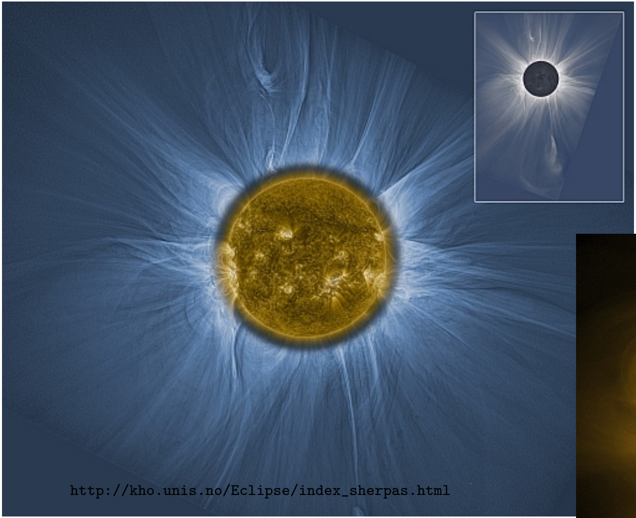
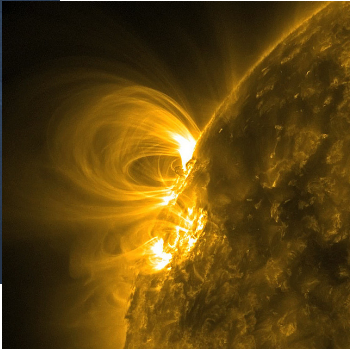
Coronal loops





Methods for 3D loop reconstruction

Stereoscopy

- An indirect approach for deriving the 3D magnetic field shape in the corona
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Multi-view B-spline Stereoscopic Reconstruction (MBSR)

- developed and implemented by B. Inhester @ MPS
- retrieves the 3D information of curve-like objects (coronal loops, prominences, leading edge of the CMEs)
- two & three view directions $\rightarrow$ N views
- reconstructs directly smoothed 3D curves using only tie-point data as input

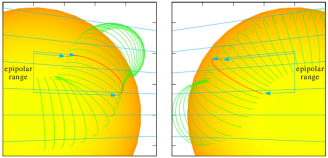
Multi-view B-spline Stereoscopic Reconstruction

1. The epipolar geometry

- stereo base line, angle, plane
- epipolar plane/line

2. Identification and matching

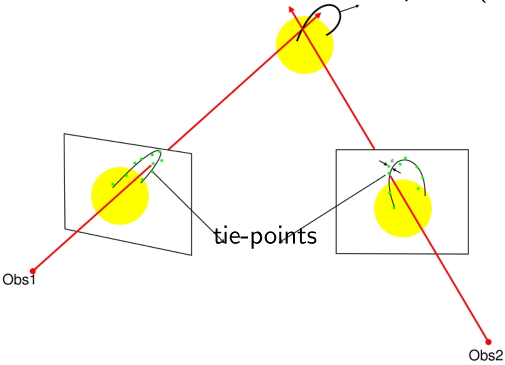
- automatic
- by visual inspection



Inhester(2006)

3. Reconstruction

loop approximated by a 3D B-spline **c**(s,**q**)



The least– square code minimizes

$$\sum_{\text{images } j} \sum_{\text{tie-points i}} |P_j \cdot \mathbf{c}(s_{i,j};\mathbf{q}) - \mathbf{x}_{i,j}|^2 + \mu \int |\frac{d^2}{ds^2} \cdot$$

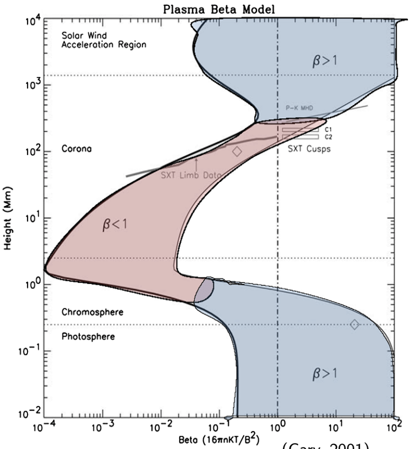
Magnetic field extrapolations

- potential field extrapolation
- linear force-free field (LFFF)
- nonlinear force-free field (NLFFF)
- magnetohydrostatics (MHS)
- static-MHD

Nonlinear force-free field (NLFFF) extrapolation

Assumptions

- coronal structures are observed to be in steady state
  $\Rightarrow -\nabla p + \rho \mathbf{g} + \mathbf{j} \times \mathbf{B} = 0$
- $\beta << 1 \Rightarrow$ magnetic pressure dominates over the plasma pressure and gravity (Wiegelmann and Sakurai, 2012)



(Gary, 2001)

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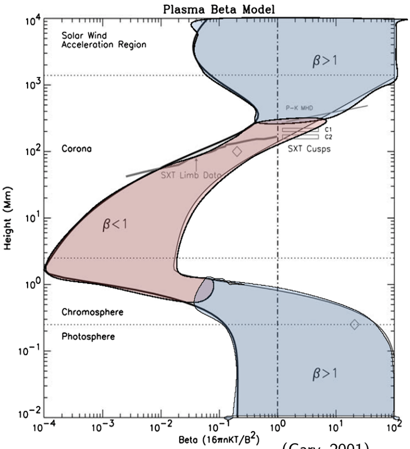
Force-free approximation

$\Rightarrow (\nabla \times \mathbf{B}) \times \mathbf{B} = 0$

$\Rightarrow \nabla \cdot \mathbf{B} = 0$



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NLFFF method

- Input: vector magnetic field
- Mostly applied for single AR, filaments
- Shortcomings:
  - condition that $\beta << 1$ does not hold in the photosphere and low chromosphere
  - ill-posed problem: the resulting B field is more affected by errors in the boundary data, the higher the altitude above the surface

Methods to extrapolate NLFFF from boundary data:

- Grad-Rubin Method (Grad & Rubin 1958; Sakurai 1981)
- Magnetofrictional method (Choudra & Schlüter 1981)
- Greens function method (Yan & Sakurai 2000)
- Optimization method (Wheatland et al. 2000)

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Nonlinear Force-Free Field optimization method

⇒ initially propose by Wheatland, Sturrock & Roumeliotis, 2000
⇒ extended and implemented by Wiegelmann, 2004; Wiegelmann and Inhester, 2010; Tadesse et al., 2011

$$L = \frac{1}{V}\int_V w_f \frac{|(\nabla\times\mathbf{B})\times\mathbf{B}|^2}{B^2}\, d^3r + \frac{1}{V}\int_V w_f |\nabla\cdot\mathbf{B}|^2\, d^3r + \frac{1}{V}\int_S (\mathbf{B}-\mathbf{B}_{obs})\cdot \mathrm{diag}(\sigma_{\mathrm{q}}^{-2})\cdot(\mathbf{B}-\mathbf{B}_{obs})\, d^2r$$

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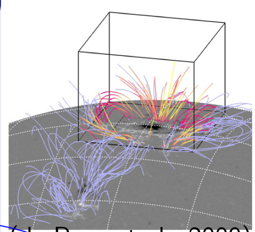

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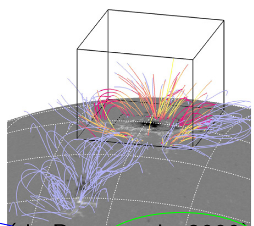
⇒ extended by Chifu et al., 2015 → S-NLFFF



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3D Coronal loop reconstruction with Machine Learning

Motivation

⇒ S-NLFFF: method using 3D stereoscopically reconstructed loops for the NLFFF extrapolation (Chifu et al., 2015, 2017) → quality of the magnetic field model increased

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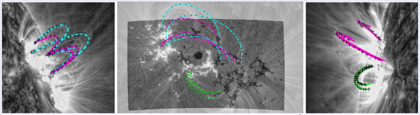

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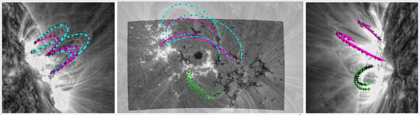

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⇒ Solution: we developed a method which uses only one view image for the 3D reconstruction of the coronal loops (Chifu and Gafeira, 2021 ApJL 910 L10)

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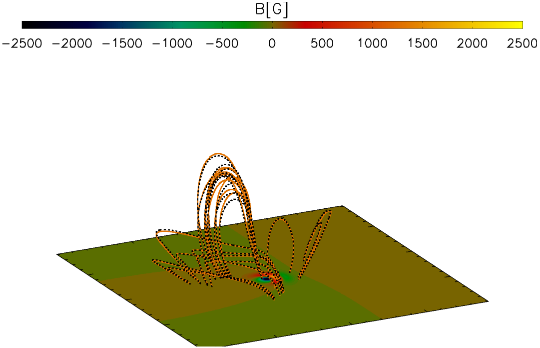
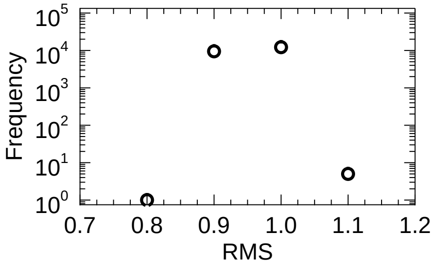
⇒ The neural network method uses 80% of the input loops as training set and the rest of 20% as validation set

Case 0

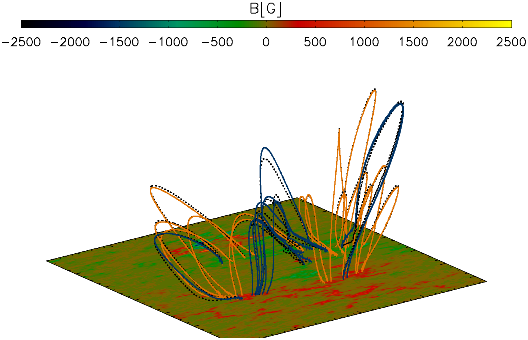
- NLFFF in Cartesian coordinates to a semi-analytic Low & Lou boundary data
- computational box 192x192x96
- From the NLFFF solution - 21704 magnetic field lines (black dashed line)
- Orange solid lines: CNN reconstructed loops
- RMS of the ratio between the CNN reconstructed and original loops

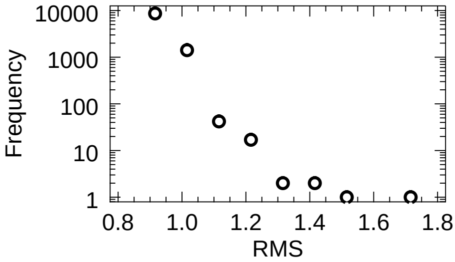




Case 1

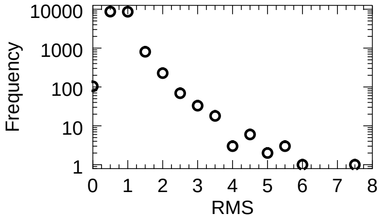
- NLFFF in Cartesian coordinates to a HMI/SDO boundary data
- computational box: 1280x400x320
- From the NLFFF solution - 10127 magnetic field lines (black dashed line)
- CNN reconstructed loops: orange (RMS <1.1) and blue (RMS > 1.1)
- 99.06% with $0.9 <$ RMS <1.1

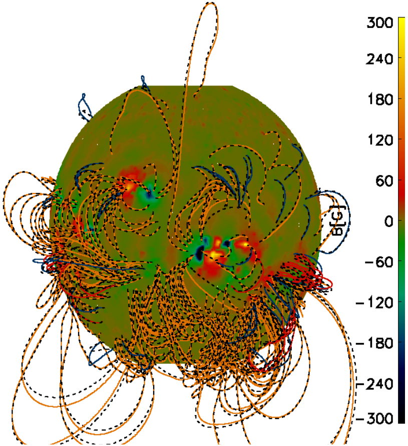




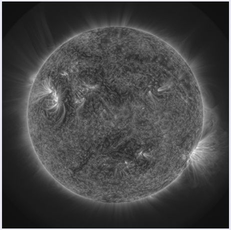
Case 2

- NLFFF (spherical coordinates) to a synoptic vector magnetogram;
- computational box 180x270x720
- From the NLFFF solution - 18555 magnetic field lines (black dashed line)
- CNN reconstructed loops: orange (0.5< RMS <1.5), blue (0< RMS <0.5) and red (1.5< RMS <2.)
- 94.5% with 0.5< RMS <1.5





How will this actually work?



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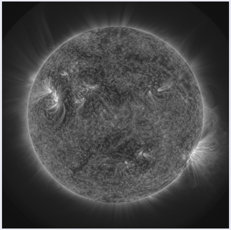

Extract info of all visible loops → Neural network → 3D loops

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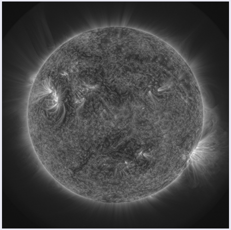

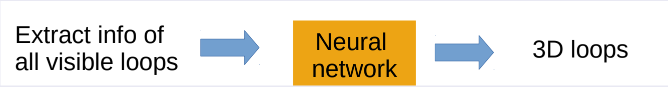

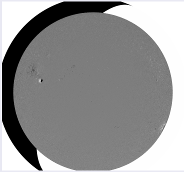

$+$ 3D loops $\Rightarrow$ S-NLFFF

Conclusion

The Convolutional Neural Network method for the 3D loop reconstruction based only on the 2D information retrieves solutions which can be further used with confidence for constraining the magnetic field modelling.

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Thank you !