Understanding Plasma Flows in Solar Active Regions: a neural network based method for the recovery and analysis of coherent plasma structures in magnetically dominated environments

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Introduction

Space weather (SW) is driven by high energy events in the solar atmosphere, e.g. solar flares (SFs) and coronal mass ejections (CMEs). These events occur in strong active regions (ARs) in the solar atmosphere. Measuring and understanding these events is paramount to forecasting when significant SW events will occur. Recent advances in high performance computing has enabled the simulation of emerging flux tubes throughout the entirety of the Sun's convective region into the lower atmosphere with the R2D2 code (see Hotta and Iijima, 2020). Assimilation of these data, along with the application of machine learning (ML) techniques such as the DeepVel (DV, see Ramos, 2017) neural network (NN), allows us to estimate realistic photospheric plasma velocities, surrounding strong magnetic fields, at small scales and with greater precision than existing methods (see Lennard et. al., in review), e.g. Fourier-Local Correlation Tracking (FLCT, see Fisher and Welsch, 2008). By training DV with data from R2D2, we are able to estimate high resolution velocities and derive the finite-time Lyapunov exponent (FTLE) fields (see Haller, 2014), which details repelling structure in the plasma flow, hence providing a skeleton for the flow. It has been shown that changes in these structures coincide with changes in the magnetic structure of the photosphere (see Chian et. al., 2019) and that these changes can be observed some time before the emergence of a strong magnetic flux (see Silva et. al., 2023). By applying these methods to our recovered velocity fields, we are able to detect a signals in the plasma flow for identifying ARs and tracking their motion throughout the photosphere by observing changes in the the flow structure through the FTLE fields. This, in theory, could be used for the identification and therefore improved observation of ARs.

Data and Model

Surface data from the R2D2 simulation [see Hotta and Iijima, 2020] shown in Fig. 1 has been used to study photospheric flows throughout the evolution of a strong emerging flux. The simulation uses a set of radiative MHD equations and follows the evolution of a magnetic flux tube, placed at -30Mm relative to the photosphere, in a realistic box which covers the entire depth of the convection region (-200Mm).

Methodology

Velocities were recovered using the DV neural network (NN) and compared with the widely used Fourier local correlation tracking (FLCT) [Fisher and Welsch, 2008] algorithm. The NN was trained to reproduce photospheric velocities from 2 time-consecutive intensity images. The NN approach presents many benefits (see Fig. 3) over FLCT since the network learns spatial relationships between flows. As shown, DV is able to recover source and sink regions accurately and also give insight to regions of vorticity. It also presents over a 100x speedup after training, compared with FLCT.
With recovered velocities, there still remains the problem of analysing these in order to determine classify the dynamics of different regions. In order to detect different flow dynamics we determine the flow skeleton by means of seeking the most repelling and attracting material surfaces, which act as transport barrier for which no fluid elements can pass through. A way of finding these is calculating the FTLE (see Eq. 1) field [Haller, 2014]. In forward (fFTLE) time, ridges in the FTLE field present the most repelling structures in flow. In backward (bFTLE) time these ridges present the most attracting structures, see Fig. 4. Typically the bFTLE ridges coincide with intergranular lanes and the fFTLE ridges pass over the centre of granules, and they can be used to determine other structures. Therefore the FTLE ridges provide a skeleton for determining the dynamics of the flow field.
Fig. 5 shows the evolution of the 20-minute fFTLE distribution at key points in the life of the AR. The distribution mean, over the AR, is shifted more to 0 as the AR grows, and after the peak the distribution returns to one more typical of the QS. This change is due to the reduction in the fFTLE field over the pore, where a large repelling structure (consistent with an Evershed flow) surrounds the pore and there is little/no repelling behaviour inside. The difference in the mean has been tracked throughout the simulation and presented in the video (see the QR code)

Video of tracking an active region by measuring changes in flow, measured by difference in mean 20-minute fFTLE value. When the difference in reaches a certain threshold, the corresponding region will light up. This first-of-a-kind approach reveals that DeepVel provides accurate velocities for recovering the flow dynamics around an AR

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The full details of this work can be found in the paper "Analysing the Recovery of Coherent Structures using DeepVel in an Active Region" (in review)

Abraham C-L Chian et al., Supergranular turbulence in the quiet Sun: Lagrangian coherent structures, Monthly Notices of the Royal Astronomical Society, Volume 488, Issue 3, September 2019, Pages 3076–3088, https://doi.org/10.1093/mnras/stz1909
Andres Asensio Ramos et al, DeepVel: Deep learning for the estimation of horizontal velocities at the solar surface, A&A, Volume 604, Article A11, July 2023, https://doi.org/10.1051/0004-6361/201730783
George Fisher and Brian Welsch, FLCT: A Fast, Efficient Method for Performing Local Correlation Tracking, arXiv, December 2007, https://arxiv.org/abs/0712.4289
George Haller, Lagrangian Coherent Structures, Annual Review of Fluid Mechanics, Volume 47:137-162, January 2015, https://doi.org/10.1146/annurev-fluid-010313-141322
H Hotta, H Iijima, On rising magnetic flux tube and formation of sunspots in a deep domain, Monthly Notices of the Royal Astronomical Society, Volume 494, Issue 2, May 2020, Pages 2523–2537, https://doi.org/10.1093/mnras/staa844
Suzana Silva et al, Novel Approach to Forecasting Photospheric Emergence of Active Regions, Astrophysical Journal Letters, https://doi.org/10.3847/2041-8213/acd007

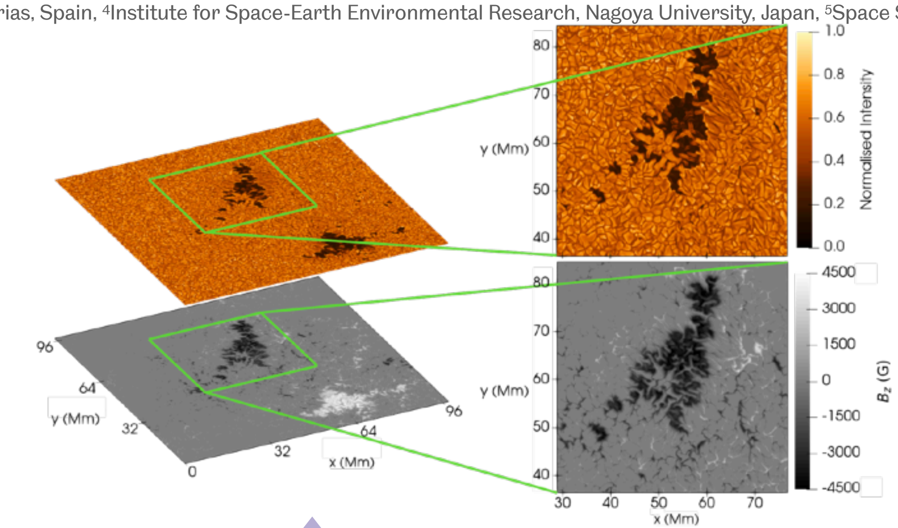

Figure 1. Example frame of surface data, at time of peak magentic flux, from R2D2. Top shows radiative intensity, bottom the magnetic field.

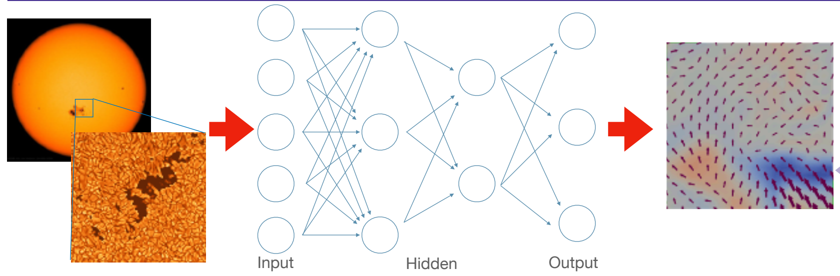

Figure 2. Sketch of NN performing recovery. Intensitygrams with velocity are used for training. New data is fed to the network and DV produces associated 2D velocity field.

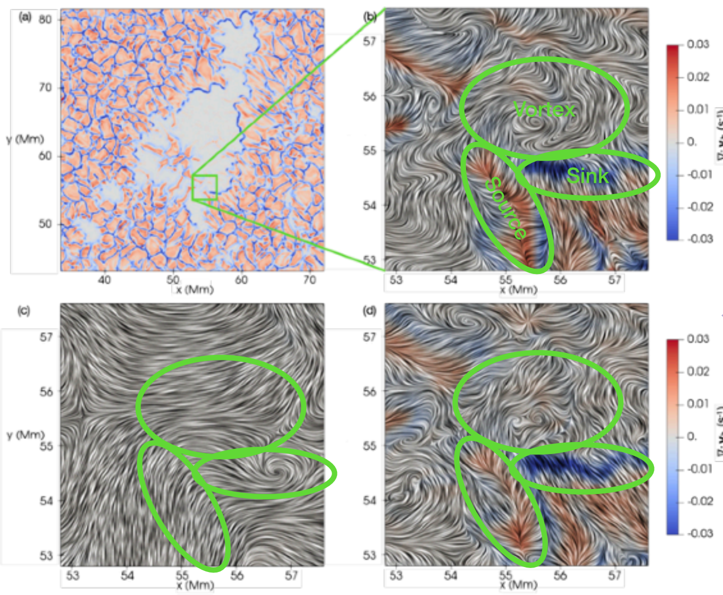

Figure 3. Example of divergence field (a) from simulation at time of peak flux, with a zoom of the flows of the highlighted region with (b) the target flows, (c) FLCT recovered flows, (d) DeepVel recovered flows.

$$D\,\phi_{t_0}^{t_0+\tau}(\mathbf{x}_{i,j}) = \begin{pmatrix} \dfrac{x_{i+1,j}(t_0+\tau) - x_{i-1,j}(t_0+\tau)}{x_{i+1,j}(t_0) - x_{i-1,j}(t_0)} & \dfrac{x_{i,j+1}(t_0+\tau) - x_{i,j-1}(t_0+\tau)}{y_{i,j+1}(t_0) - y_{i,j-1}(t_0)} \\ \dfrac{y_{i+1,j}(t_0+\tau) - y_{i-1,j}(t_0+\tau)}{x_{i+1,j}(t_0) - x_{i-1,j}(t_0)} & \dfrac{y_{i,j+1}(t_0+\tau) - y_{i,j-1}(t_0+\tau)}{y_{i,j+1}(t_0) - y_{i,j-1}(t_0)} \end{pmatrix}$$

$$\mathrm{FTLE}_i^{t_0+\tau}(\mathbf{x}) = \frac{1}{|\tau|} \ln \sqrt{\max(\lambda_i)}, \quad i = 1,2$$

Equation 1. The FTLE is found by computing the maximal eigenvalues λ of the Jacobian matrix for particles $\mathbf{x}_{i,j}$ in the flow.

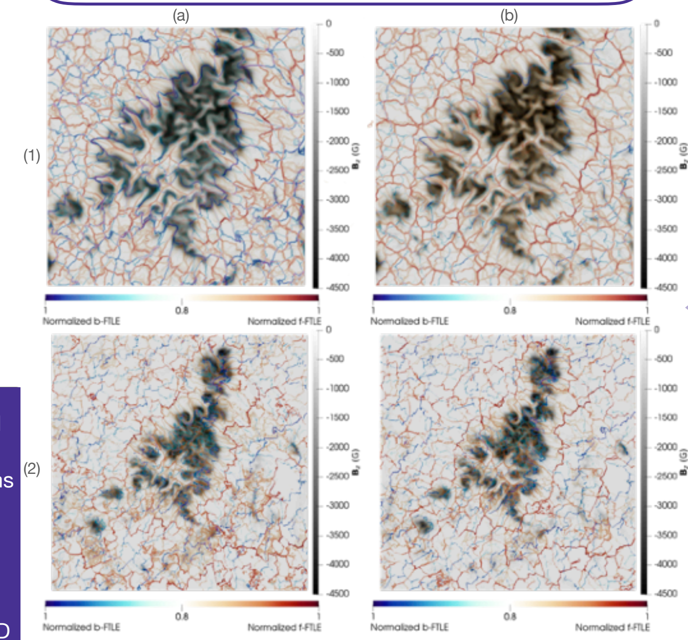

Figure 4. Row (1) shows the 20 minute (granular scales) recovered FTLE fields (forward in red, backwards in blue) superposed on the magnetic field. Row (2) shows the 100 minute (mesogranular scales) recovered FTLE fields. Column (a) is generated using velocities from the simulation, (b) shows is generated using the velocities recovered by DV.

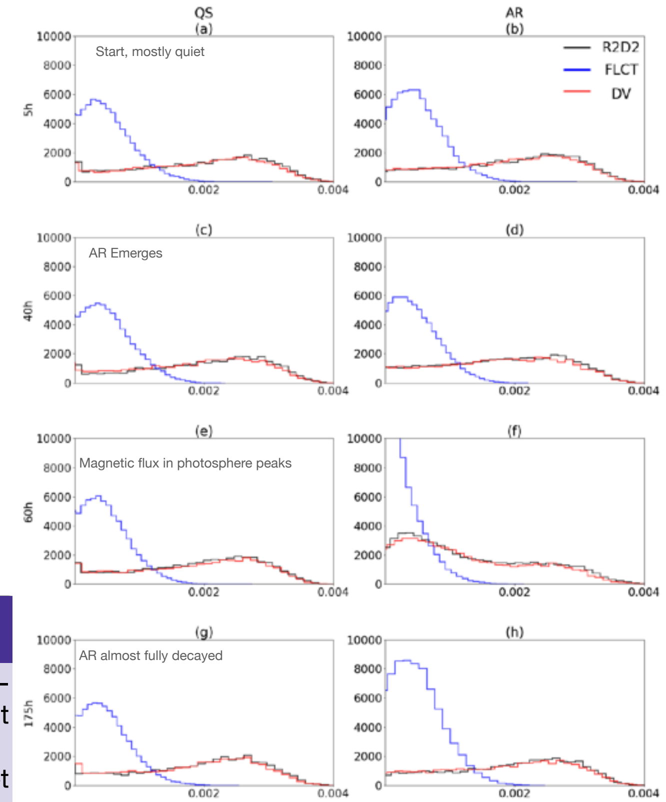

Figure 5. Evolution of 20 minute fFTLE field distribution generated from simulation (black), FLCT (blue) and DV (red), over a QS patch and an AR

Results

- DV is able to provide quick and accurate horizontal velocities from 2 time-consecutive continuum intensity images and is able to reproduce coherent structures present in simulation data at the length scale of solar granules (<1Mm).
- Active regions, as previously found, display different flow dynamics to typical quiet Sun (QS) regions, determined by the flow skeleton described by the finite-time Lyapunov exponent (FTLE) field.
- Emergence of an AR displays an initial complication in flow structure and then a distinct simplification after emergence.
- Flow structures inside ARs appear more vortical, on small scales, than surroundings providing further means to identify ARs independent of magnetic structure.
- Structures in flow presented in the FTLE field are similar to those seen in Evershed flows, seen in observations.
- Differences in the FTLE field between ARs and QS provides a signal for locating flow structures that are typical of ARs.

Future Work

- Test on observational data matching simulation resolution (~0.1") and test predictive capability of methodology.
- Test DV on low resolution (~1") data from SDO/HMI over entire solar disc.
- In depth study of evolution of plasma flow dynamics throughout AR lifetime.
- Make improvements accuracy of DV for detecting the smallest possible changes and improve speed structure detection.