

QUEEN'S

BELFAST

UNIVERSITY

Accurately constraining velocity information from spectral imaging observations using machine learning techniques

Conor D. MacBride¹ and David B. Jess¹

¹Astrophysics Research Centre, School of Mathematics and Physics, Queen's University Belfast, Belfast, UK

Abstract

Determining accurate plasma velocities from spectroscopic measurements is a challenging endeavour, especially when considering weak chromospheric absorption lines are often rapidly evolving and contain multiple plasma profiles in their composition. Here, Mr MacBride presents a novel method that employs machine learning to identify the underlying components present within an observed spectral line, before constraining the constituent profiles through Gaussian and/or Voigt fits, alongside minimisation tests to validate the reliability of the results. With this method, automatic adjustments can be made to the models fitted such that active and quiescent components present in each particular spectrum can be identified accurately. Lastly, Mr MacBride utilises a Ca II 8542 Å spectral imaging dataset of a sunspot as a proof-of-concept study to show the potential of his team's method for reliably extracting two-component atmospheric profiles that are commonly present in dynamic sunspot umbral chromospheres.



Introduction

Having accurate velocity information for plasma in the solar atmosphere is important for studying the properties of waves present within. Using spectroscopic measurements of the Sun, velocities can be found by calculating the Doppler shift of a particular absorption line core**[1]**.

Different spectral lines are formed across different atmospheric heights, therefore, by choosing a particular line, waves at a particular atmospheric height can be studied**[1,2]**. Some spectral lines, including Ca II 8542 Å, include an active emission component as well as the quiescent absorption component. Separate absorption and emission profiles must be fitted to each spectrum. The fitted profiles are then used to find the Doppler velocities of the quiescent/active atmospheric components.

Preliminary profile fitting methods struggled to accurately fit a profile across every region of a sunspot's umbra. This was due to the spectra having a variety of different profiles due to the active component that was often present among the quiescent component.



Figure 3: A time-distance diagram of the quiescent umbral Doppler velocities (right panel), extracted from a one-dimensional slice taken through the middle of the sunspot umbra (solid red line; left panel). The solid yellow line in the left hand panel represents the umbra-penumbra boundary used to isolate the umbral regions.

Method

find stationary_wavelength

Determine the stationary wavelength from the average spectrum of a quiescent region.

apply corrections to Spectra

find & subtract background from Spectra

A constant background is subtracted from each spectrum, calculated from the average value of the spectrum's wings over ± 20 timesteps to filter noise out.

train & test NeuralNetwork

Manually classify 200 sample spectra (100 for training, 100 for testing) into classes shown in Figure 2.

classify Spectra using NeuralNetwork

foreach Spectrum in Spectra:

Fit an absorption Voigt (Eq. 1) profile**[3]** to each spectrum of class **0** or **1**. Error bars are created to lower the priority of fitting the noisy wings. (Fig. 5)

 $V(x;\sigma,\gamma) = \int_{-\infty}^{\infty} G(x';\sigma)L(x-x';\gamma) \ dx'$ Equation 1: Voigt profile[3] with

Gaussian G and Lorentzian L centered at origin.

Even if emission was not present in a particular spectrum, the fit would still "improve" if the algorithm fitted a significant non-zero emission profile as it could filter out some noise in the absorption profile.

Figure 1: Plot showing the velocities found for the Ca II 8542 Å line spectra inside a sunspot's umbra at a particular time. Their classifications are shown in Figure 2.

Machine Learning

Using machine learning, spectra can be accurately classified into discrete categories based on the ratio of their active component to their quiescent component. This allows the fitting method to be tailored to the physics that is present in each spectrum.



if class is 0:

fit AbsorptionVoigt to Spectrum (peak & slopes)

Fitting noisy peak detail is less important than fitting the slopes, therefore, wavelengths around the stationary line core are now given larger errors.

if class is 1:

fit AbsorptionVoigt to Spectrum (slopes)

Both an absorption Voigt profile and an emission Voigt profile will be fitted to each spectrum of class 2, 3 or 4. (Figure 4)

if class is 2, 3 or 4:

fit AbsorptionVoigt + EmissionVoigt to Spectrum (slopes)

find velocity using fitted_line_core & stationary_wavelength

Using the line cores of the fitted absorption profiles and the stationary wavelength, the Doppler velocities are calculated. (Figure 2 and Figure 3)

save velocity & fitted_parameters to file







Figure 4: Example fit of a spectrum of class **4**. Sigma profile represented by shaded areas. *Left:* Combined profile. *Right:* Absorption profile and emission profile plotted separately.

 8541.0 8541.5 8542.0 8542.5 8543.0 8543.5 Wavelength (Å)
 Figure 5: Example fit of a spectrum of class 0. Sigma profile represented by shaded areas.

References

[1] David Jess et al. 2019, *Nat. Astron.*[2] Krishna Prasad et al. 2017, *ApJ*, **847**, 5
[3] Mofreh Zaghloul 2007, *Mon. Not. R. Astron. Soc.*, **375**, 1-6

Acknowledgements

Mr MacBride would like to acknowledge the support of the Department for the Economy (Northern Ireland) through their postgraduate research studentship.



Conor MacBride

cmacbride01@qub.ac.uk
 conor@macbride.me
 macbride.me



Scan for a video of Figure 1 throughout time, more details and instructions on how to use this software yourself, **or visit**:

macbride.me/specfit