Exploring the Sun’s upper atmosphere with neural networks: Reversed patterns and the hot wall effect

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ABSTRACT

We have developed an inversion procedure designed for high-resolution solar spectro-polarimeters, such as those of Hinode and the DKIST. The procedure is based on artificial neural networks trained with profiles generated from random atmospheric stratifications for a high generalization capability. When applied to Hinode data, we find a hot fine-scale network structure whose morphology changes with height. In the middle layers, this network resembles what is observed in G-band filtergrams, but it is not identical. Surprisingly, the temperature enhancements in the middle and upper photosphere have a reversed pattern. Hot pixels in the middle photosphere, possibly associated with small-scale magnetic elements, appear cool at the log \( \tau_{500} \approx -3 \) and \(-4 \) level, and vice versa. Finally, we find hot arcs on the limb side of magnetic pores. We interpret them as the first piece of direct observational evidence of the “hot wall” effect, which is a prediction of theoretical models from the 1970’s.

Key words. Sun: photosphere – Sun: faculae, plages – Sun: magnetic fields – sunspots – methods: numerical – methods: data analysis

1. Introduction

Inversion techniques allow us to retrieve information encoded in spectral lines about the atmospheres where they form. A wide variety of strategies have been employed for decades in solar physics to interpret spectroscopic and spectropolarimetric observations (see e.g., the reviews by del Toro Iniesta & Ruiz Cobo 2016; Bellot Rubio 2006; Socas-Navarro 2019). Most applications are based on the least-squares fitting of the observed spectral lines with synthetic profiles, which are computed from model atmospheres whose parameters are iteratively adjusted until a satisfactory fit is attained. However, advances in instrumentation are driving an increasing interest in the exploration of alternative methods. Two-dimensional spectropolarimetry is now very common and fast growing data rates motivate the exploration of new algorithms that have the potential of being faster and/or more robust for a systematic application.

Artificial neural networks (ANNs) offer a promising new approach for many purposes where profile fitting is inadequate because one needs a faster or a more robust performance. The first applications of ANNs in solar physics are almost 20 yr old, dating back to Carroll & Staude (2001) and Socas-Navarro (2002). However, while those first efforts produced encouraging results, ANN inversions were not immediately adopted by the community for mainly two reasons. First, disentangling the magnetic filling factor from the intrinsic field strength has proven extremely challenging, as noted since those early works (Socas-Navarro 2003). The magnetic field tends to exhibit small-scale structures in the solar photosphere. In arc-second resolution observations, it is common to find pixels where the magnetic field occupies less than 10% of the resolution element. This area fraction is referred to as the filling factor and it introduces an important complication for ANN inversions. Second, a more practical issue is the complexity involved in the coding of algorithms for the training of an ANN model.

Those early problems have been largely resolved in recent years, leading to a renewed interest in ANNs (e.g., Liu et al. 2020; Guo et al. 2020; Díaz Baso & Asensio Ramos 2018; Asensio Ramos & Díaz Baso 2019; Sainz Dalda et al. 2019; Felipe & Asensio Ramos 2019; Milić & Gafeira 2020; Gafeira et al. 2021). Current and upcoming instrumentation are delivering very high resolution observations, mitigating the filling factor problem. Furthermore, there has been a tremendous development in the field of deep learning and many sophisticated tools have been made publicly available to simplify the problem of building and training ANNs (e.g., Abadi et al. 2015; Paszke et al. 2019).

In this paper we use a relatively simple ANN model and take a different approach than previous work for the training strategy. Instead of using a simulation snapshot as the starting point for a training set, as in Asensio Ramos & Díaz Baso (2019) or Milić & Gafeira (2020), we create a database of profiles from random stratifications of the relevant parameters. This provides a wider coverage of the parameter space and guarantees that the ANN is not specialized on any particular scenario. Unlike Asensio Ramos & Díaz Baso (2019), whose ANN performs a full inversion of the entire 2D field at once, this ANN works on each pixel independently. In that regard, it is more similar to a traditional inversion technique. We call this procedure DIANNE2.0 (Direct Inversion with Artificial Neural Networks), which is in line with our previous work.

We created two different ANNs, one to invert photospheric observations from DKIST/ViSP (Daniel K Inouye Solar Telescope/Visible Spectro-Polarimeter, see Rimmele et al. 2020) and the other one for the Hinode satellite’s SOT/SP (Solar Optical Telescope/Spectro-Polarimeter). DKIST/ViSP data are not yet available so we focus here on the analysis of the Hinode inversions. After testing the procedure with synthetic data and previous inversions of real observations, we applied it to Hinode...
observations of active regions. In this manner we obtained dat-
acubes with a fairly unique combination of high spatial resolu-
tion, a large field of view, and depth-dependent temperatures. 
These maps show a fine hot network in active regions, particu-
larly around sunspots and pores.

We find some surprising results in this application, such as 
an anticorrelation between hot pixels in middle and upper lay-
ers. Also, the inversions reveal a series of hot arcs running along 
the limb side of pores in the observed regions. We interpret these 
arcs as the first direct observation of the “hot wall” effect, a pre-
diction of fluxtube models from the work of Spruit (1976) which 
had not been directly observed before.

2. The ANN model and training set

All the calculations presented in this paper were produced with 
relatively standard computer hardware. We employed a Linux 
workstation powered by eight 3 GHz Intel Xeon cores. The sys-
tem is equipped with a GTX 1080 GPU that handles most of 
the ANN-related processing. Our ANN model and codes are pub-
licly available1 in a repository.

The ANN is created and trained using PyTorch (Paszke et al. 
2019). It is a simple multilayer perceptron with six hidden lay-
ers between the input and output layers. Each hidden layer com-
prises 300 neurons. The input layer has a number of neurons that 
matches the number of spectral pixels in a given profile (175 for 
DKIST/ViSP and 112 for Hinode SOT/SP). The output layer has 
9 neurons, which correspond to the output parameters that we 
wish to retrieve. These parameters are as follows: five tempera-
tures at different heights, three components of the magnetic field 
vector, and a single-valued line-of-sight velocity. In all cases, the 
activation function chosen is a leaky ReLU (Maas et al. 2013).

The entire training procedure takes a few hours on our hardware 
described above.

For the training and validation sets, we computed one million 
synthetic profiles from randomized model atmospheres. A thou-
sand models and profiles were considered as the validation set 
and the rest were used for training. These models were obtained 
as random variations from four different reference atmospheres, 
mainly the following: HSRA (Gingerich et al. 1971), VAL-C (Vernazza 
et al. 1981), FAL-C (Fontenla et al. 1993), and the 
sunspot model M of Maltby et al. (1986). We provide here 
a description of the randomization procedure in some detail 
because the construction of this database is critical for the ANN 
to be able to perform adequately when faced with real observa-
tions and to exhibit good generalization properties.

For each relevant parameter, we took the stratification in the 
reference atmosphere and added a depth-dependent perturbation 
to it. The perturbation was constructed by assigning values to 
certain layers and then interpolating in depth. In the case of the 
temperature, the parameter to which spectral lines are most sen-
sitive, we started by creating a perturbation in four layers. These 
layers are not necessarily the same heights that the ANN will 
retrieve. They are equispaced in the logarithm of continuum optical 
depth at 500 nm (log \( \tau_{500} \)) and their actual location is dif-
f erent for the four reference atmospheres. The perturbations at 

1 At the time of writing this paper, there was no publicly avail-
able DKIST/ViSP observations and we had no means of testing our 
procedures. Because of that, we have postponed the release of the 
DKIST/ViSP ANN model until we are able to verify it. The training 
set generator is available.

2 https://github.com/hsocasnavarro/DIANNE2.0

these four points are drawn from a Gaussian distribution with 
a 1500 K standard deviation. From these four values, the depth-
dependent perturbation was interpolated to the entire grid and 
added to the reference model. With the new thermal stratifica-
tion, the model is set in hydrostatic equilibrium and the equation 
of state is solved to compute plasma densities, ionization frac-
tions, relevant molecules, and electron densities. These opera-
tions are part of a standard NICOLE calculation. Details may be 
found in Socas-Navarro et al. (2015).

For the magnetic field, the \( B_i \) (the line-of-sight component) 
is linear in log \( \tau_{500} \), whereas \( B_x \) and \( B_y \) (the transverse com-
ponents) are constant with height. Furthermore, \( B_z \) is defined by 
\( B_z(0) \), its value at log \( \tau_{500} = 0 \), and its gradient. We constructed 
three possible scenarios with weak, strong, and extreme fields, 
having probabilities of 45%, 45%, and 10%, respectively. The 
field strength \( B_z(0) \) takes values from a uniform distribution with 
a width of 500, 2000, and 6000 G for the weak, strong, and 
and extreme fields, respectively. The sign for each field component 
is randomly set to ±1 except for \( B_z \), which is always considered 
positive. Since the Zeeman effect has a 180-degree ambiguity in 
the transverse component of the field, we restrict our solutions to 
the subspace with positive \( B_z \). The \( B_z \) gradient is set to either 0 
or a random value, with a 50% probability. The random value is 
taken from a uniform probability distribution between −150 and 
150 G per unit in log \( \tau_{500} \).

The filling factor (\( \alpha \)) is set to 1 in 50% of the models. The 
rest have a uniform distribution between 0.1 and 1. In addition to 
the filling factor, we consider a fixed amount of stray light in the 
instrument by adding an average quiet Sun profile to Stokes I. 
The amount of stray light is fixed to 10%, which is a typical 
value for spectrographs.

This training set was built with the purpose of covering a 
sufficiently wide range of profiles for the ANN to work with 
all possible observations of the solar photosphere in the 630 nm 
spectral window observed by Hinode. The statistical distribution 
of our random atmospheres is not necessarily optimal. We relied 
on past experience and numerical experimentation to determine 
a suitable set. A systematic analysis is beyond the scope of this 
work.

We used NICOLE (Socas-Navarro et al. 2015) to compute 
synthetic Stokes profiles for the entire set of one million ran-
don models in the database. The synthesis parameters for one 
of the training sets were defined to mimic Hinode/SP observa-
tions. DKIST/ViSP will also feature a preset mode to observe 
the same 630 nm window so we produced another similar set of 
profiles simulating those observations in anticipation of its sci-
cence operations. Both training sets are publicly available in the 
repository mentioned above.

The Stokes profiles are fed as inputs to the ANN. For the 
outputs, we extracted a set of nine parameters from the random 
model atmospheres in the database. These parameters are as fol-
lows: five temperatures (\( T_1, \ldots, T_5 \)), extracted at optical depths 
log \( \tau_{500} = 0, \ldots, -4 \), a bulk Doppler velocity (\( v_\phi \)), and the three 
components of the pixel-averaged magnetic field (\( F_x, F_y \), and \( F_z \), 
where \( F_i = \alpha B_i \) for \( i = x, y, z \)). We do not aim here to disentan-
gle the filling factor \( \alpha \) from the intrinsic magnetic field strength 
(\( B_i \)) in the magnetic element. We seek to retrieve the magnetic 
flux density (\( F \)) in the resolution element, which simplifies the 
problem.

3. Comparisons with other inversions

After successfully training the ANN and observing a good recov-
ery of the validation set (see Fig. 1), we tested it with real
As noted in previous work (Socas-Navarro 2005), a good performance with the validation set composed of synthetic observations does not guarantee a good operation with real data.

Ideally, one would like to have inversions of Hinode/SP data to compare with our ANN. Unfortunately, there are very few inversions of Hinode/SP maps that yield the height stratification. The standard pipeline includes an inversion carried out by the instrument team with the MERLIN code (Lites et al. 2007), which is based on the Milne-Eddington approximation and therefore does not provide information on the height dependence of any physical quantities. One of the few inversions with the height stratification existing in the literature is that of Socas-Navarro (2011) using NICOLE (later refined in Socas-Navarro 2015).

We took the same Hinode/SP observations used for the NICOLE inversions and processed them with our ANN. The NICOLE inversions took about 5 h on a dedicated parallel run over the eight cores of our workstation. The ANN inversion was completed in half a second.

A comparison of the maps produced by the ANN and those from NICOLE (the 2015 version) is presented in Figs. 2 and 3. The similarity between the spatial structures in the images obtained with both techniques is remarkable. The NICOLE inversions are much noisier, especially in the higher layers. ANNs are known to have good noise filtering properties. In this case, most of the noise in the NICOLE data is “inversion noise” produced by the specific \( \chi^2 \) fitting procedure that seeks the best fit to the entire line profile. The upper layers are probed only by the core of the spectral lines. Since the core occupies very few pixels in the spectral profile, there is very little information about those upper layers. For very similar profiles, the \( \chi^2 \) minimization might reach a slightly different solution where the core is fitted with more or less accuracy, perhaps compensating for it with a better fit to other spectral regions. The end result is a pixel-to-pixel variation that becomes more important in those
layers where the profile is less sensitive. This problem could be mitigated by fine-tuning the weights, giving more weight to the pixels that carry the relevant information. However, different layers would require a different optimization.

The ANN, on the other hand, “learns” what the optimal spectral points are that it needs to focus on for each layer. There is a direct, deterministic mapping between the observations and the inversion result. For that reason, the ANN maps (right column in the figures) look cleaner. We can even see some of the residual defects in the data reduction that are still present in the observations as they propagate directly into the results.

Although the left and right panels are very similar, there is a systematic offset between the two. To remove this offset, we applied an additional postprocessing renormalization on each ANN output, so that the average value and the dispersion with respect to the average match those of the NICOLE inversions. This was done to remove, at least to first order, some small residuals that arise in the application to real data. The postprocessing is the same for all inversions; it may be viewed as an empirical calibration of the ANN.

We do not find these residuals in the validation tests so they must be due to systematic differences between our synthetic training set and the real observations, such as observation artifacts, differences in the PSF, or an inaccurate estimate of the stray light used in the synthesis. A detailed analysis of these residuals is beyond the scope of this paper; however, for our purposes here, this simple renormalization, which is the same for all observations, resolves the issue.
Fig. 3. Comparison of inversions of a Hinode map performed with NICOLE (left) and our ANN (right). Positive (negative) velocities are directed downwards (upward). Positive (negative) magnetic polarity represents fields pointing up (down) from the solar surface.

The normalization factors for $T_0, \ldots, T_4$ are 0.90, 1.26, 1.29, 1.44, and 1.60, respectively. The growing trend of these factors indicates that the ANN produces models that are, on average, steeper than those obtained with NICOLE. The synthesis tests presented below demonstrate that the model atmospheres obtained in this manner produce spectral profiles very similar to the observations. For the magnetic field (see below), this calibration yields a factor of 0.7 in all three components. We incorporated this normalization factor in all subsequent inversions.

The similarity between both sets of images confirms that NICOLE and the ANN are giving consistent results. This test should not be viewed as NICOLE giving the “correct” answer and our ANN being an approximation. Both techniques are approximations and the difference between them is the sum of their respective errors.

The accuracy of the ANN in recovering the magnetic field is not relevant for the purposes of this paper. Nevertheless, we show here similar comparisons for the sake of completeness. We processed two active region maps observed with Hinode/SP (more details are in Sect. 5.2 below). These maps are $384 \times 384$ (map1) and $871 \times 512$ (map2) spatial pixels. The ANN inversions took 4 and 11 s, respectively. Standard inversions with the MERLIN code are available for these maps. Figures 4 and 5 show the comparison of the magnetic flux inferred by MERLIN and our ANN. MERLIN is a Milne-Eddington inversion code. As such, it does not work with temperatures or other physical thermodynamic parameters of the atmosphere but with the fundamental radiative transfer parameters, such as the line strength, Doppler width, Doppler shift, monochromatic source function, and magnetic field. All of these parameters are assumed to be constant in height except for the source function, which is assumed to vary linearly with monochromatic optical depth. Thus, we can only compare the magnetic field and line-of-sight velocity produced by our ANN with those from MERLIN. For consistency with the training set, the 180-degree ambiguity is resolved by choosing the solution that has a positive component along the x axis.
Fig. 4. Comparison of inversions of a Hinode map (map1) performed with MERLIN (left column) and our ANN (center). The color scale is the same for both inversions. Scatter plots are shown in the right column. Positive (negative) magnetic polarity represents fields pointing up (down) from the solar surface. The heliocentric angle is $\mu = 0.79$.

4. Reconstruction fits

A common problem with ANN-based inversions is that they are not based on fitting the observations, unlike $\chi^2$ fitting methods. The quality of a fit is usually a good indicator to assess the validity of the results. Our approach suffers from this limitation as well, but it does provide enough information to reconstruct a model atmosphere and, from there, synthesize spectral profiles that can then be compared to the observations. It does not provide the same information as a fit because the reconstruction of the atmosphere implies additional approximations. Nevertheless, it is still useful information.

We took the parameters from the ANN inversion and computed model atmospheres by interpolating them in optical depth. For the temperature stratification, we performed a cubic interpolation of the five temperatures between $\log \tau_{500} = 0$ and $-4$. Above $\log \tau_{500} = -4$, we imposed that the stratification became flat. In the deeper layers below $\log \tau_{500} = 0$, the temperature gradient usually becomes steeper. After some experimentation, we concluded that a gradient that is 30% larger than between $\log \tau_{500} = 0$ and $-1$ works best in reproducing the observations. Hydrostatic equilibrium was imposed and the plasma equation of state was solved numerically to determine gas and electron densities, ionization stages, and relevant molecules. The magnetic field and bulk Doppler velocities are considered as constant with height from the ANN inversion.

We computed the synthetic profiles from the models reconstructed from the ANN outputs, obtaining the results shown in Fig. 6. These “reconstruction fits” support the notion that the temperature stratification retrieved by the ANN is consistent with the observations. The first panel shows the average profiles over the entire region. The other three are selected representative samples of profiles having a value of $\chi^2$ equal to the median over the region, and the median plus or minus a standard deviation of all $\chi^2$ values.

Figure 7 shows the reconstructed profiles from the model returned by the ANN for a pixel with a strong magnetic field and exhibiting features of an unresolved highly-redshifted second
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Fig. 5. Comparison of inversions of a Hinode map (map2) performed with MERLIN (left column) and our ANN (center). The color scale is the same for both inversions. Scatter plots are shown in the right column. Positive (negative) magnetic polarity represents fields pointing up (down) from the solar surface. The heliocentric angle is $\mu = 0.88$.

magnetic component. These anomalous profiles are not present in the training data. This test demonstrates that the ANN exhibits good generalization properties and is capable of retrieving a sensible approximation, representative of the main atmospheric component.

5. Results

We employed the ANN-based inversions described in the previous sections to explore the thermal stratification of the solar photosphere. The maps discussed above are in agreement with previous works in showing a rich thermal structure, rapidly changing with height. In this paper, we compare the spatial distribution to what is observed in the Ca II or G-band filtergrams.

5.1. Quiet Sun

We start by considering the quiet Sun map inverted in the tests of Sect. 3. The maps are $200 \times 200$ pixels, but the field of view is not exactly square because the slit stepping, which establishes the sampling in the $x$-direction, does not necessarily match the pixel size. In this case, the sampling reported in the file headers is $0.15 \times 0.16$ arc-seconds per pixel.

The first recognizable pattern that stands out is the similarity of the mid-photosphere temperature map to the Doppler velocity distribution. This is the well known reversed granulation effect, a natural consequence of convective motions. The tightest correlation in our dataset, shown in Fig. 8, is between a temperature at $\log \tau_{500} = -2$ and the Doppler velocity ($v_z$), with a Pearson’s correlation coefficient of 0.45; it is important to recall that, as noted above, the velocities retrieved by our procedure are at the base of the photosphere. Reversed granulation is also characterized by an anticorrelation with the $\log \tau_{500} = 0$ map, which in our data is of $-0.37$.

The scatter plot exhibits some vertical features. These are the result of the ANN assigning nearly the same value of $v_z$ to many different profiles instead of smearing them over the uncertainty range of that parameter. In least-squares inversions, the solutions for similar profiles tend to spread over the error bar for that parameter because each inversion has followed a different path on the $\chi^2$ hypersurface. However, an ANN might end up assigning a specific value for a parameter (or a narrow range of values) as a “sticky solution” for a range of input profiles. This means
that the resulting maps are usually less noisy, but the noise level should not be considered an indication of the uncertainties.

The temperature maps retrieved in the ANN inversions show a different network structure at each atmospheric height. Bright photospheric networks have been observed in the wings of the Ca\u208ii lines and in the G-band, which are also accessible to Hinode’s narrow band instrument (Hinode/NB). It is then of interest to investigate whether these structures are related to those, both in the quiet Sun and active regions.

5.2. Active regions

In this section we analyze two large-field active-region maps for which there exists simultaneous G-band and Ca\u208ii imaging. The datasets were acquired on January 11, 2010 around 18:30 UT (map1) and January 22, 2012 around 06:30 UT (map2). The spatial sampling is coarser than in the quiet Sun observations (0.30 and 0.32 arc-seconds in the x and y directions, respectively) to encompass a larger field of view. Map1 consists of 384 x 384 spatial pixels, while map2 consists of 871 x 512. The full maps are shown in Figs. 10 and 11, with the various panels displaying temperatures at various heights, along with the narrow-band images (the magnetic field was already introduced in Figs. 4 and 5).

The data show a fine network of hot pixels that roughly follows, in the mid-photosphere, the magnetic field distribution (log $\tau_{500} = -1$ and $-2$). It is more patchy higher up the structure and this does not follow the magnetic field maps. Each layer exhibits a different structure and, more importantly, they also differ from both the G-band and Ca\u208ii H images. We discuss these differences below.

A reversal of hot and cool areas between the middle and the upper photosphere is also apparent. For instance, the lower left corner of both maps (Figs. 10 and 11) is cool at log $\tau_{500} = -1$, but hot at log $\tau_{500} = -4$ (upper left and upper right panels in both figures). The same anticorrelation is apparent in the upper left and lower right corners of map2 (Fig. 11). In fact, most of the region left of $x = 200$ arc-sec in Fig. 11 has a reversed appearance. The hot network at log $\tau_{500} = -1$ (upper left panel) is seen as a dark shadow at log $\tau_{500} = -4$ (upper right panel). The same

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\textsuperscript{3} https://hesperia.gsfc.nasa.gov/ssw/hinode/sot/doc/guide/SAGv3.3.pdf
is true about the area left of \( x = -240 \) in map1 (Fig. 10). We quantified this by selecting only the pixels that are hot in either layer (\( T > 5400 \) at \( \log \tau_{500} = -1 \) or \( T > 5000 \) at \( \log \tau_{500} = -4 \)) and computing the Pearson’s correlation coefficient. The values obtained are \(-0.77\) in map1 and \(-0.78\) in map2.

The temperature maps do not match the narrow-band images. There is some similarity between the temperature at \( \log \tau_{500} = -1 \) and the \( G \)-band image in the overall distribution of the hot network. However, a closer look shows important differences (see discussion of Fig. 12 below).

The comparison with the Ca II H images is even more puzzling. The Ca emission follows the pattern of the hot pixels in the mid-photosphere at \( \log \tau_{500} = -1 \) instead of the upper photosphere, as one would have expected; it is important to recall that, as discussed above, the distribution of hot pixels at \( \log \tau_{500} = -4 \) is anticorrelated with that at \( \log \tau_{500} = -1 \). However, the Ca images show a small-scale filamentary structure in the network, as opposed to the chains of dots that appear in the temperature maps. The appearance of filaments would suggest that we are seeing higher layers, but the brightness distribution follows that of the mid-photosphere. We speculate that the most plausible explanation is that both the low photosphere and the (low) chromosphere contribute to the response function of this spectral band. Detailed radiative transfer modeling would be necessary to confirm this point, but it would require some knowledge of the chromospheric conditions, which is not available from these data.

Figure 12 shows a zoom on two regions containing several pores in both maps. The magnification is different in each figure because the area with pores is larger in map2. Even though the \( G \)-band bright points extend over the same area as the hot network at \( \log \tau_{500} = -1 \), they do not exhibit the same features when seen at high resolution.

A very remarkable feature in these images is the presence of a bright arc around the edge of pores, tracing the limb side (the arrows indicate the direction to the closest limb). These arcs are visible around virtually every pore in both datasets. They have a width of one or two pixels, suggesting that they are not fully resolved in the observations, and their temperature is always between 5600 and 5700 K. By contrast, the pores have

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**Fig. 9.** Comparison of temperatures at different heights, as retrieved by the ANN inversion, to Ca II filtergram (bottom right panel) in a quiet Sun region.
temperatures mostly of 4600–4800 K; however, in some cases, particularly for the larger ones in map2, they may go down to 3600 K, such as in the feature at coordinates (1 65 390) of map2.

The bright arcs are probably the pores’ “hot walls”. The idea of a hot wall seen in perspective was introduced in early fluxtube models to explain the center-to-limb variation of faculae and G-band points (Spruit 1976; Knoelker & Schuessler 1988; Topka et al. 1997). Spruit’s original work considered unresolved fluxtubes and small pores of up to 1000 km. The pores in our observations are significantly larger, starting from roughly 3500 km, but there is no reason why the same effect should not take place in them.

6. Verifications

The results presented in the previous section have important implications. Since they were obtained using a novel technique, they should be subject to as much scrutiny as possible. First we consider the question of whether the spectral lines analyzed are sensitive to layers as high as $\log \tau_{500} = -4$. To address this issue, we computed the response functions (Beckers & Milkey 1975; Caccin et al. 1977) to the temperature. Figure 13 shows the wavelength and height dependence of the temperature response at one of the hot wall locations.

The figure shows that the line cores are mostly sensitive to the heights around $\log \tau_{500} = -2$. This is the reason why if we
make a monochromatic image at the wavelength of the line core, we obtain a picture very similar to the map of the temperature at log \( \tau_{500} = -2 \). However, even though it is not the dominant contribution, there is information about the log \( \tau_{500} = -3 \) and -4 heights. The magnitude of the response function in the upper photosphere is on the order of \( 10^{-2} \) K\(^{-1}\). Therefore, observations with a noise level of \( 10^{-3} \) may have a sensitivity of \( \Delta T \sim \Delta I/R_T \approx 100 \) K at a single wavelength.

In addition to the response functions, the most conclusive piece of evidence that the ANN is able to extract this information and provide a reliable reconstruction of those layers is the fact that, when compared to the NICOLE inversion in Fig. 3 (upper panels), we can see that both codes produce the same patterns; however, it is important to notice that the ANN output in the figure is shown before the calibration normalization and thus there is an offset between both maps. There is no reason why two different codes based on completely different procedures and working independently would produce the same spatial distribution of features if they were mere artifacts.

The next important question is whether the finding of hot walls, as temperature enhancements on the limb side of the pores, is reliable. We used NICOLE as an independent verification of the ANN inversions in two selected locations representative of two pixels on opposite sides of a pore. One of these pixels corresponds to a hot wall solution, while the other is a normal, non-enhanced pixel on the opposite side of the pore. The two locations are marked by arrows in Fig. 14.

The NICOLE inversion gives results consistent with those of the ANN. Both atmospheres have similar temperatures at the base of the photosphere, but the blue (hot wall) model grows increasingly hotter with height than the orange (quiet) model. At the log \( \tau_{500} = -1 \) level, NICOLE retrieves a temperature of 5430 K for the hot wall and 5040 K for the quiet pixel. The ANN gives 5660 and 5080 K for those same pixels, respectively.
Fig. 12. Enlargement of the areas with pores in the active regions map1 (upper panels) and map2 (lower panels). The left panels show ANN temperature reconstructions at log(τ_500) = −1 and the right panels, the respective G-band filtergrams. Notice the bright arcs around the limb-side (indicated by the orange arrow) of the pores in the left panels.

Thus, NICOLE inversions confirm the presence of a temperature excess on the limb side of the pore.

7. Conclusions

ANN-based inversions are enabling the analysis of large spectroscopic, and spectropolarimetric, datasets. One such application is presented in this paper. The training strategy appears to be sufficiently robust for application to real observations in various situations.

It is puzzling to find such a clear anticorrelation in the location of hot points in the middle and upper photosphere. This is counterintuitive and warrants further work to confirm it since it appears to challenge the generally accepted idea that small magnetic elements act as channels to propagate energy into the upper atmosphere (e.g., Jefferies et al. 2006; Rajaguru et al. 2019). One possibility is that the energy dissipation and associated heating might occur at higher layers than we observe here. That would explain the presence of hot points at intermediate heights that do not exhibit a temperature enhancement in the upper photosphere. However, this would not explain the patches with hot points in the upper layers that appear to be quiet lower down.

In our ANN approach, each pixel is inverted independently of the rest. Therefore, the spatial distributions obtained cannot be artifacts of the procedure; they must be present in the data somehow. A possible mundane explanation for the pixels that are hot in middle layers and quiet at the top could be that the ANN is not properly trained for such situations and the closest models in the training set that reproduce the lower and middle layers are quiet in the upper layers. However, that would not explain the opposite scenario in the anticorrelation, that is to say the patches with a quiet lower and middle photosphere having an enhanced temperature in the upper layers.

Another important result presented in this paper is the first observation of the “hot wall” effect, which has been a model prediction since the 1970’s (Spruit 1976) and it explains the bright appearance of small magnetic elements. The original theoretical models considered smaller pores of up to 1000km, but we have detected it here in structures of at least 3500km. Hot walls are believed to be responsible for the brightness of faculae and small magnetic flux elements (e.g., Topka et al. 1997).
the same values within a broader uncertainty range, creating the vertical features seen in the scatter plot of Fig. 8. Finally, we would like to mention a negative result. In spite of our best efforts with this approach, we have not been able to retrieve gradients in the magnetic field or the Doppler velocity. We have encountered the same inability to retrieve gradients in previous works with other ANNs. It is not clear to us whether this inability is due to a specific problem with our methodology or an intrinsic limitation of the procedure. An interesting line for future work would be to explore these and other limitations.

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References

Abadi, M., Agarwal, A., Barham, P., et al. 2015, TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems, software available from tensorflow.org

Asensio Ramos, A., & Díaz Baso, C. J. 2019, A&A, 626, A102

Beckers, J. M., & Milkey, R. W. 1975, Sol. Phys., 43, 289

Bellot Rubio, L. R. 2006, in Solar Polarization 4, eds. R. Casini, & B. W. Lites, ASP Conf. Ser., 358, 107

Caccan, R., Gómez, M. T., Marmolino, C., & Severino, G. 1977, A&A, 185, 621

Carroll, T. A., & Staude, J. 2001, A&A, 378, 316

del Toro Iniesta, J. C., & Ruiz Cobo, B. 2016, Liv. Rev. Sol. Phys., 13, 4

Díaz Baso, C. J., & Asensio Ramos, A. 2018, A&A, 614, A5

Felipe, T., & Asensio Ramos, A. 2019, A&A, 632, A82

Fontenla, J. M., Avrett, E. H., & Loeser, R. 2001, ApJ, 546, 319

Gafeira, R., Orozco Suárez, D., Milic, I., et al. 2021, A&A, 651, A31

Gingerich, O., Noyes, R. W., Kalkofen, W., & Cuny, Y. 1971, Sol. Phys., 18, 347

Guo, J., Bai, X., Deng, Y., et al. 2020, Sol. Phys., 295, 5

Hunter, J. D. 2007, Comput. Sci. Eng., 9, 90

Jefferyes, S. M., McIntosh, S. W., Armstrong, J. D., et al. 2006, ApJ, 648, L151

Knoeller, M., & Schuessler, M. 1988, A&A, 202, 275

Lites, B., Casini, R., Garcia, J., & Socas-Navarro, H. 2007, Mem. Soc. Astron. It., 78, 148

Liu, H., Xu, Y., Wang, J., et al. 2020, ApJ, 894, 70

Maas, A. L., Hannun, A. Y., & Ng, A. Y. 2013, in ICML Workshop on Deep Learning for Audio, Speech and Language Processing

Maltby, P., Avrett, E. H., Carlson, M., et al. 1986, ApJ, 306, 284

Milic, I., & Gafeira, R. 2020, A&A, 644, A129

Paszke, A., Gross, S., Massa, F., et al. 2019, in Advances in Neural Information Processing Systems 32, eds. H. Wallach, H. Larochelle, A. Beygelzimer, et al. (Curran Associates, Inc.), 8024

Pérez, F., & Granger, B. E. 2007, Comput. Sci. Eng., 9, 21

Rajaguru, S. P., Sangeetha, C. R., & Tripathi, D. 2019, ApJ, 871, 155

Rinnele, T. R., Warner, K., Keil, S. L., et al. 2020, Sol. Phys., 295, 172

Sainz Dalda, A., de la Cruz Rodríguez, J., De Pontieu, B., & Gošić, M. 2019, A&A, 626, A67

Sanz Dalda, A., de la Cruz Rodríguez, J., De Pontieu, B., & Gošić, M. 2019, ApJ, 875, L18

Socas-Navarro, H. 2002, in SOLMAG 2002. Proceedings of the Magnetic Coupling of the Solar Atmosphere Euroconference and IAU Colloquium 188, 11–15 June 2002, Santorini, Greece, ed. H. Sawaya-Lacoste, ESA SP-505, (Noordwijk, Netherlands: ESA Publications Division), 45

Socas-Navarro, H. 2003, Neural Networks, 16, 355

Socas-Navarro, H. 2005, ApJ, 621, 545

Socas-Navarro, H. 2011, A&A, 529, A37

Socas-Navarro, H. 2015, A&A, 577, A25

Socas-Navarro, H. 2019, in Advanced Solar Polarimetry - Theory, Observation, and Instrumentation, ed. M. Sigworth, ASP Conf. Ser., 236, 487

Socas-Navarro, H., de la Cruz Rodríguez, J., Asensio Ramos, A., Trujillo Bueno, J., & Ruiz Cobo, B. 2015, A&A, 577, A7

Spruit, H. C. 1976, Sol. Phys., 50, 269

Topka, K. P., Tarbell, T. D., & Title, A. M. 1997, ApJ, 484, 479

Van Der Walt, S., Colbert, S. C., & Varoquaux, G. 2011, Comput. Sci. Eng., 13, 22

Vernazza, J. E., Avrett, E. H., & Loeser, R. 1981, ApJS, 45, 635

This view, which is now the community consensus, is strongly reinforced by our data.

Our results open the possibility of a future application to chromospheric lines. The chromosphere is much more complicated to simulate due to NLTE (non-Local Thermodynamic Equilibrium) radiative transfer, much faster and vigorous dynamics, faster wave phase velocities, etc. As a result, magneto-hydrodynamical numerical models are not yet sufficiently realistic that they can be used to match the observations and this limits the ability to train an ANN with chromospheric simulated profiles. However, our training strategy does not require a full numerical model. In principle, one could apply a similar training using semiempirical 1D models with random perturbations to produce a large number of NLTE profiles. The computational effort involved in the database generation would be significantly higher than here, but it is still feasible.

An area of improvement that we have found with this technique is the “sticky solution”, where the ANN basically returns

![Fig. 13. Upper panel: response function to the temperature at the core of the 630.1 nm line. The vertical scale was chosen to show the sensitivity range in the upper photosphere. Lower panel: decimal logarithm of the (unsigned) response function to the temperature as a function of the wavelength and height.](image1)

![Fig. 14. NICOLE inversions of two spectra observed at a pore boundary, one being in the hot wall (blue line) and the other on the opposite side (orange line). Upper left: observed profiles in the hot wall (blue) and the opposite side (orange), Lower right: temperature stratification produced by NICOLE for the hot wall (blue) and the opposite side (orange) spectra.](image2)