“Computational Intelligence for Stellar Magnetic Fields Parameter Determination”

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ABSTRACT

Nowadays there are plenty of astronomical databases available, containing enormous quantities of raw data. Hence, analysis and automatic extraction of relevant information from these has become a crucially important task. In this work, we present the first results of applying an algorithm which enables automatic determination of a couple of parameters from polarized stellar spectra: effective temperature (Teff) and mean longitudinal magnetic field (Heff). Our method is based on supervised learning for artificial neural networks. For this purpose, we first generated a synthetic database of polarized stellar spectra using the code COSSAM. The database consists of the spectra derived from **43 different magnetic models** each one corresponding to a different combination of parameters (4 free parameters). Then, we characterize the performance of the algorithm for the inference of the parameters of interest, Heff and Teff, at different levels of signal-to-noise ratio. Considering the previously mentioned 43 different atmospheric models, a total of **2402 individual spectra** were synthesized using the **COSSAM** code which, after proper processing, were used to conduct the proper training of our neural network. In this work we will present the first results of the network performance under a supervised regime.

AIMS

Our final goal is to achieve a good efficiency in our algorithm to retrieve both parameters: Heff and Teff, to subsequently apply it to a big database of real objects (http://polarbase.irap.omp.eu/).

After further development, we also expect to be able to retrieve at least a couple of parameters associated with the dipole geometry

METHOD

In order to achieve our goal, we first generated a ‘big’ database of artificial spectra. To do so, we first obtained the Castelli & Kurucz Models and used the code ATLAS12_ada (translated from the original version of R. Kurucz by K.M. Bischof and debugged, streamlined and extended by M.J. Stift) to obtain the the Stift Atmospheric Models.

Then we used this models, each defined by a combination of several parameters (Teff, log g, macro turbulent velocity and metallicity), to create all of the individual spectrum using the code COSSAM (Stift – Könighofer). Each of this spectra is defined by 6 free parameters: *Atmospheric Model, the Geometry of the Dipole, Dipole Moment, Rotational parameter, Pulsational parameter and a spacial grid*. Just like the Atmospheric model, all of these parameters, except the dipole moment, are dependent of some other parameters, for instance the geometry is defined by the Euler Angles of the system among others. For this work, we kept some of these parameters constant looking to simplify the process. The final database is integrated as shown on Table 1.

Database
- Atmospheric Models
- Stellar Spectra
- Noise
- Multi Zeeman Signatures (MZS)

Artificial Neural Network
- Multilayer Perceptron
- K-Fold Cross Validation
  - K=5

After we had our full database, then we add different levels (5%,10%,20% and 30%) of white Gaussian noise to it. Then we used Principal Component Analysis and Zeeman Doppler Imaging multi line technique to obtain the **Multi Zeeman Signatures** (MZS) of each of the clean and noisy spectra.

Finally we used this database (including all the five noise levels: 0-30%) to train our Artificial Neural Network (ANN). We used the Stokes I Signatures to train one ANN to obtain Teff and Stokes V signatures to obtain Heff.

For display purposes, we only show the results for the Heff regression, but results for Teff are equally good.

RESULTS

Regression and Error Histogram are shown in Figures 1 and 2 respectively. Errors were calculated using several statistical measures, results are shown in Table 2.

Atmospheric Models				
Parameter	**Initial Value**	**Step**	**Final Value**	**TOTAL**
T_{eff}	5000	500	7000	5
log g	1	1	5	5
V_{turb}	0	-	2	2
Metallicity : 0.07834 / 0.07810				
TOTAL : 43				

Table 1

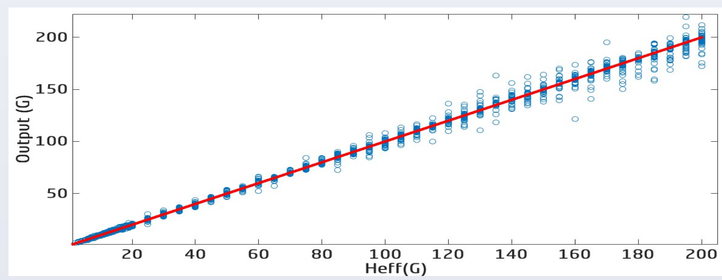

Figure 1

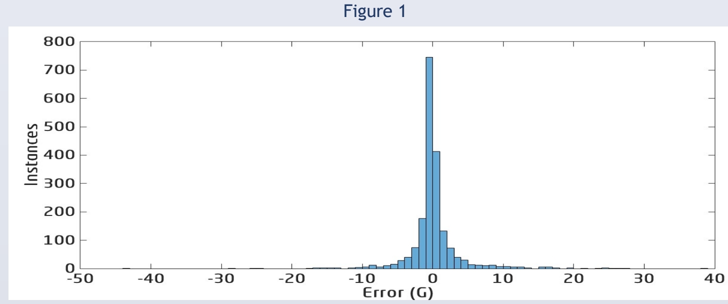

Figure 2

	Clean	5% Noisy	10% Noisy	20% Noisy	30% Noisy	Combined
R	1	0.9997	0.9981	0.9957	0.9919	0.9983
MSE	0.37×10^{-3}	2.2525	15.4002	35.7429	66.6803	13.6181
RMSE	0.0180	1.4991	3.9234	5.9735	8.1564	3.6651
RRSE	0.28×10^{-3}	0.0234	0.0612	0.0932	0.1273	0.0572
MAE	0.0151	0.9294	2.2574	3.4641	4.6954	1.8141
RAE	0.26×10^{-3}	0.0164	0.0397	0.0609	0.0826	0.0319

Table 2

ACKNOWLEDGMENTS and CONTACT

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