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The stellar parametrization using Artificial Neural Network

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Abstract. An update on recent methods for automated stellar parametrization is given. We present preliminary results of the ongoing program for rapid parametrization of field stars using medium resolution spectra obtained using Vainu Bappu Telescope at VBO, Kavalur, India. We have used Artificial Neural Network (ANN) for estimating temperature, gravity, metallicity and absolute magnitude of the field stars. The network for each parameter is trained independently using a large number of calibrating stars. The trained network is used for estimating atmospheric parameters of unexplored field stars.

Keywords : stellar abundances, ANN, absolute magnitude

1. Introduction

The stellar spectra even at modest resolution contain wealth of information on stellar parameters. In fact, most of the classification work has been done using medium/low resolution spectra. Hydrogen lines are good indicators of temperature and luminosity for a good range in spectral types; although for hotter end stars lines of neutral and ionized helium, carbon and nitrogen are used while strengths of molecular features are employed for the cool stars. A recent summary of the advances in classification can be found in Giridhar (2010). Additional features such as near IR triplet at 7771-74Å and Ca II lines in 8490-8670 Å region are also used for luminosity calibration.

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Many large telescopes are now equipped with multi-object spectrometers enabling coverage of a large number of objects per frame for stellar systems like clusters. Instruments such as 6df on the UK Schmidt telescope and AAOMEGA at the AAT can provide very large number of spectra per night. On-going and future surveys, and space missions would collect a large number of spectra for stars belonging to different components of our Galaxy. Such large volume of data can be handled only with automatic procedures which would also have the advantage of being objective and providing homogeneous data set most suited for Galactic structure and evolutionary studies. Another outcome would be detection of stellar variability and finding of peculiar objects.

2. Automated methods for parametrization

Several methods have been developed to estimate atmospheric parameters from medium-resolution stellar spectra in a fast, automatic, objective fashion. The most commonly adopted approaches are based upon the minimum distance method (MDM) and those using Artificial Neural Network or ANN. Both the approaches use reference libraries to make comparison with object spectra. Other methods use correlations between broadband colors or the strength of prominent metallic lines and the atmospheric parameters e.g. Stock & Stock (1999).

2.1 Comparison between empirical and synthetic libraries

The observed stellar spectra are assigned a given spectral type and Luminosity Class (LC) based upon the appearance of spectral features and hence these classifications are not model dependent. Synthetic spectra depend on model atmospheres mostly assuming local thermodynamic equilibrium (LTE), are affected by inadequacy of atomic and molecular database and non-LTE effects are severe for certain temperature/metallicity domain. Empirical spectra however may not have the required uniform range in the parameter space.

2.2 MDM based approaches

The basic concept is to minimize the distance metric between the reference spectrum and spectrum to be classified/parametrized. The accuracy depends upon the density of reference spectra in parameter space. We need to construct a stellar spectral template library for stars of known parameters. The software TGMET developed by Katz et al. (1998) is based upon direct comparison with a reference library of stellar spectra. Soubiran et al (2003) used this approach to estimate the $T_{\rm eff}$, log g and [Fe/H] with very good accuracy 86 K, 0.28 dex and 0.16 dex respectively for good S/N ratio spectra of F, G and K stars. Instead of reference spectra synthetic spectra using the model atmospheres were used by Zwitter et al.(2008) and others. In SPADES (Posbic et al. 2011) the comparison is made of specific lines allowing abundance determination of various elements.

2.3 Artificial Neural Network

A very good account of this approach can be found in numerous papers e.g. Bailer-Jones (2002), von Hippel (1994) and others. It is a computational method which can provide non-linear mapping between the input vector (a spectrum for example) and one or more outputs like T_{eff}, log g and [M/H]. A network need to be trained with the help of spectra of stars of known parameters. The trained network is used to parametrize the unclassified spectra. We have used the back-propagation ANN code by Ripley (1993). The chosen configuration of ANN is described in Giridhar, Muneer & Goswami (2006).

3. Analysis of VBT spectra

We had initiated a modest survey program for exploration of metal-poor candidate stars from HK Survey (Beers, Shectmann and Preston 1992), EC survey (Stobie et al. 1997) and high proper motion list of Lee (1984). The semi-empirical approach based upon the strengths of prominent lines and line ratio adopted in Giridhar & Goswami (2002) resulted in detection of several new metal-poor stars. We therefore chose to explore the use of ANN on a larger sample of candidate metal-poor stars.

The medium resolution spectra (R$\sim$2000) were obtained using OMR spectrometer with 2.3m telescope at VBO, Kavalur. The spectra cover 3800–6000 Å region. Our spectral analysis, alignment procedure etc. are described in Giridhar, Muneer & Goswami (2006). A few representative spectra arranged in increasing temperatures are presented in (Fig. 1).

3.1 Calibration accuracies of stellar parameters

Our training set containing 143 stars of known atmospheric parameters were chosen from Allende Prieto & Lambert (1999), Gray, Grahm & Hoyt(2001), Snider et al. (2001) and ELODIE data base (Soubiran, Karz & Cayrel 1998).

Fig. 2 shows the ANN results compared with calibrating values. We have shown in Figure 2a [Fe/H] ANN results for 76 calibrating stars plotted against those from literature. For the metallicity range of −3.0 to +0.3 dex. the RMS scatter about the line of unity is 0.3 dex which is similar to the intrinsic uncertainties metallicities for calibrating stars. To avoid using the same spectra for training and testing purposes,

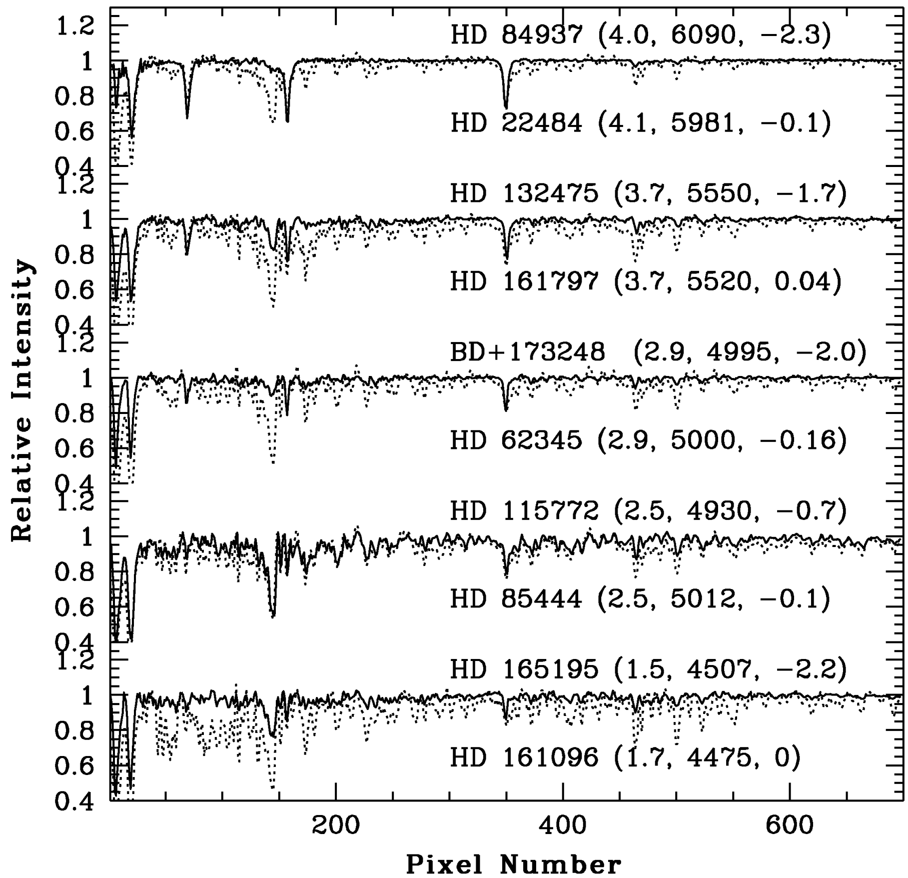

Figure 1. Sample spectra arranged in temperature sequence are presented. The stars with normal metallicity are plotted as dotted lines while metal-poor stars are shown as continuous lines.

we divided the training set into two parts and trained ANN for each part. Then the weights for part 1 were used to estimate [Fe/H] for stars in part 2 while those of part 2 were used to estimate [Fe/H] for stars in part 1. The errors shown in the Figure 2 are therefore realistic estimate of errors. This approach of dividing calibrating sample into two separate training and testing sets has been adopted for $T_{\rm eff}$ and log g calibration also.

We had good $T_{\rm eff}$ and log g estimates for 143 stars for calibrations and among them 110 stars had nearly solar metallicities while 33 were hard core metal-poor stars. While training the networks for temperature we found that usage of the same ANN for normal metallicity stars as well as metal-poor stars was giving large calibration errors (250 to 300K for $T_{\rm eff}$). It is understandable as the spectra of metal-poor stars and also those of hot stars have weak metallic lines. To overcome this degeneracy we used separate ANNs for each metallicity subgroup for the temperature (as well as gravity) calibration. The temperatures estimated by AAN are compared with the literature values in Fig. 2b. The RMS error is now reduced to 150K.

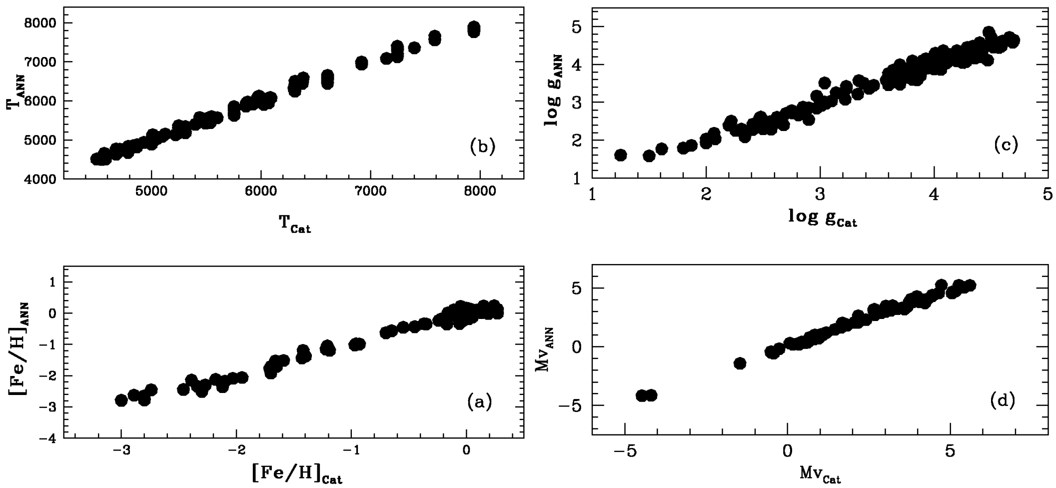

Figure 2. The parameters estimated from ANN are compared with those from literature.

The Fig. 2c shows the result for gravity calibration adopting the procedure mentioned above. The RMS error is about 0.35 for log g range of 1 to +4.5 dex.

A large fraction of stars observed by us have good parallax estimates (errors less than 20%). Combining the V magnitudes with parallaxes the distances and hence M_V could be estimated. Most of these objects were nearby objects so the effect of interstellar extinction could be assumed as negligible. Our spectral region contains many luminosity sensitive features like hydrogen lines, Mg I lines at 5172-83 Å, G bands etc. However, the same feature cannot serve the whole range of spectral types. We have divided the sample stars into two temperature groups and yet another group for metal-poor objects. The usage of three separate networks helped in attaining calibration accuracy $\sim \pm 0.3$ mag for M_V. The M_V estimated by ANN are compared with those estimated from parallaxes as shown in Fig. 2d.

4. Stellar parameters for metal-poor candidate stars

A different set of ANNs for each atmospheric parameter were trained for metal-poor candidate stars. A preliminary estimation of metallcity was made using ANN trained on the full range of metallicity. Then, we refined the measurements by using two different ANN sets; one for estimating the atmospheric parameters for stars of near solar metallicties and the other for the significantly metal-poor stars ([Fe/H] < -0.7 dex). The (B-V) colours were available for many of them which were used to verify the $T_{\rm eff}$ estimated by ANN. In most cases the temperature estimated using ANN were in close agreement with colour temperatures. A sizeable fraction of the candidate stars belonged to [Fe/H] -0.5 to -2.5 dex range.

5. Conclusions

We have demonstrated that using ANN we can measure atmospheric parameters with an accuracy of ± 0.3dex in [Fe/H], ± 200 K in temperature and ± 0.35 in log g with the help of training set of stars of known parameters. We find that independent calibrations for near solar metallicity stars and metal-poor stars decrease the errors in T_{eff} and log g by a factor of two. We have extended the application of this method to estimation of absolute magnitude using nearby stars with well determined parallaxes. Better M_V calibration accuracy can be obtained by using two separate ANNs for cool and warm stars. The present accuracy of M_V calibration is ~±0.3mag.

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