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ULTRAVIOLET STELLAR SPECTRAL CLASSIFICATION USING A MULTILEVEL TREE NEURAL NETWORK

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Abstract: Here we present a pattern classification technique based on an Artificial Neural Network (ANN) in a multi-level tree configuration to classify ultraviolet stellar spectra from the *IUE Low-Dispersion Spectra Reference Atlas*. Preliminary results of this technique show that 94% of the spectra have been classified correctly with an accuracy of one sub-class. A conventional χ^2 minimization scheme has also been applied to the data to compare the classification obtained from these schemes with that of the IUE catalog classification.

Keywords: stellar classification — galaxies — stellar content — methods — statistical — neural networks

1. INTRODUCTION

The classification of stellar spectra has recently been attempted on optical and near infrared databases with Artificial Neural Network technique using Multi Layer Back Propagation algorithm (e.g., Gulati et al., (1994); von Hippel et al., (1994); and Weaver (1994)). While in the ultraviolet (UV) region, only conventional statistical and criteria evaluation methods have been applied to classify ultraviolet (UV) spectra into ultraviolet classes (Jaschek and Jaschek, (1984); and Heck *et al.* (1986)). In fact, the UV region of the spectrum is also important in understanding the stars, particularly, the early types which exhibit most of their fluxes in the UV. Further, the comparison of the UV spectral classification with that of its optical counterpart can be used to resolve the anomalies of classification and supplement information on interstellar extinction (Gulati *et al.* (1987)).

In this paper, we present the preliminary results of the classification of stellar spectra in the ultraviolet range using the back propagation neural network technique implemented in a multi-level tree configuration. The input database and preprocessing is briefly discussed in section 2.1. Two classification schemes, namely *metric distance minimization scheme* and *multilevel tree network* are described in sections 2.2 and 2.3 respectively. Finally, section 3 contains *results* and *discussion*.

2. CLASSIFICATION SCHEMES

2.1. Input Data and Preprocessing

Out of the total database, a subset of 211 stellar spectra, ranging from O to F type stars, were selected from the *IUE Low resolution spectra reference atlas, Normal Stars* prepared by Heck et. al. (1984) (hereafter referred to as *IUE catalog*). The information in the form of flux energy distribution as a function of wavelength, and spectral classification determined by Jaschek and collaborators is used as an input for further analysis. A set of 128 spectra spanning 75 spectro-luminosity classes was treated as a template and the remaining 83 spectra were used as test set. The catalog classification of these spectra was taken from IUE catalog, where, like HD classification, the UV spectral classification is given in terms of O, B, A and F as main classes, values ranging from 0.0 to 9.5 for sub-classes and letters s, g and d for super-giants, giant, dwarfs respectively for the luminosity classes.

Each spectro-luminosity class was represented by roman number, following the coding scheme as, $x = 1000 \times A1 + 100 \times A2 + A3$, where A1 was the main spectral type of the star (i.e., O to F types coded as 1 to 4), A2 was the sub-spectral type of the star (coded from 0.0 to 9.5) and A3 the luminosity class of the star (i.e., 2, 5 or 8 for s, g or d). For example, stars dB2.5, gO9.5 and sF7 (ultraviolet classes) were coded as 2258, 1955 and 4702 respectively. A set of 35 wavelengths dictated by human expert (which have also been identified as diagnostic of the classes) was selected as input to the classification schemes as monitoring wavelengths (see Table 1 in IUE catalog). Figure 1a shows the typical stellar UV spectra for O, B, A and F type stars along with the wavelength positions, where the line depths (flux values) were monitored for ANN training and testing.

2.2. Metric Distance Minimization Scheme

The metric distance minimization scheme has been well reviewed by Kurtz (1984) and we have used this scheme on the IUE data, only for comparing the performance of the ANN technique. This technique is based on reduced $\tilde{\chi}^2$, which is defined (for no statistical weighting, (Bevington, (1969)) as

$$\tilde{\chi}^2 = \frac{\sum_{i=1}^n S_i - T_i^2}{p} \quad (1)$$

where p is the degrees of freedom, $S_i \lambda_i$ is the spectrum of one of the set of standard star spectra and $T_i \lambda_i$ is an unknown star spectrum. λ_i is a vector for n wavelength monitoring points, as is described earlier. The test stellar spectrum is compared with the set of reference spectra to compute the respective $\tilde{\chi}^2$ values. The spectral type of the reference spectrum corresponding to the minimum $\tilde{\chi}^2$ is assigned to the test spectrum. This procedure is then repeated for the remaining set of the test spectra.

2.3. The Multilevel Tree Network (MTN)

We have attempted a new technique resembling a tree structure. A three-level tree network is shown in Figure 1b. This network terminology is analogous to that of a tree. The very first node is called a *root* node which is at *level* one. Nodes at level two, which are *children* of root node, again form subtrees. Terminal nodes, which are at last level, are also called *leaf* nodes. Children of the same parent node are known as *siblings*. The MTN uses the standard MBPN (described in Gulati et al. 1994) at root and non-terminal nodes. Terminal nodes just label the final output class, they do not employ the MBPN classifier.

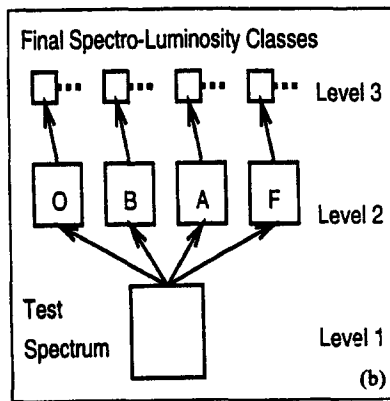
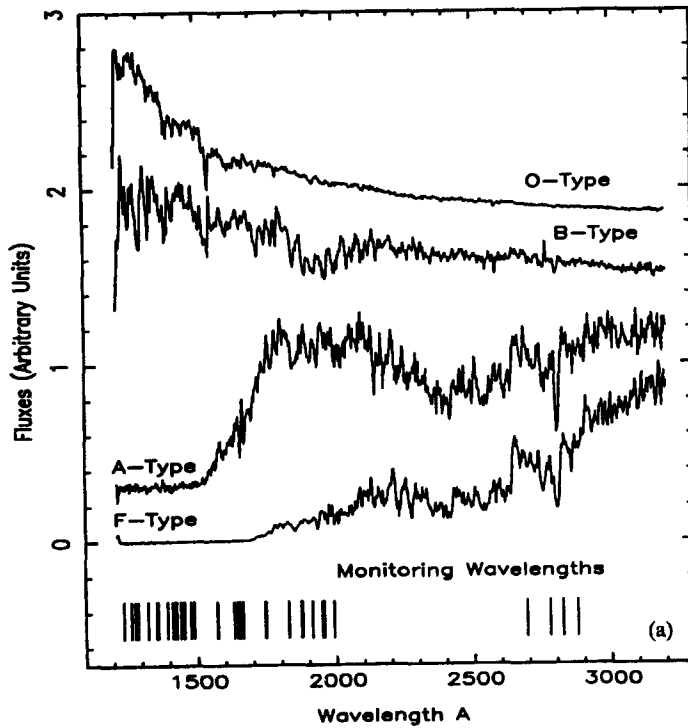


Fig. 1. (a) Four examples of UV spectra used to train the network. Vertical lines indicate 35 monitoring wavelengths. (b) Schematic of three-level tree network. Each small box represents the MBPN used for classifying spectra at the given level.

During the training session of MTN, a complete training set is presented to the root node. The classifier at the root node discriminates the whole training set into the main classes of different spectral types. The outputs of the root node classifier, represented as non-terminal nodes (see Figure 1b), further use the MBPN over the reduced training set containing only the respective main-class spectra. The siblings at level two can be computed concurrently on different machines (if one has access to

Table 1. Comparative Performance of Classification Schemes (after 3- σ rejection)

| Parameters | Catalog vs. $\bar{\chi}^2$ | Catalog vs. ANN | ANN vs. $\bar{\chi}^2$ |
|------------------|----------------------------|--------------------|------------------------|
| σ | 128.8 | 106.0 | 83.85 |
| $m \pm \Delta m$ | 1.037 ± 0.025 | 1.018 ± 0.021 | 0.998 ± 0.017 |
| $c \pm \Delta c$ | -99.99 ± 65.07 | -58.72 ± 53.95 | 5.11 ± 42.63 |
| r | 0.9776 | 0.9839 | 0.9901 |

a network of workstations). The output of each individual sibling classifier, which are represented by leaf nodes, are used to label the class of the input pattern. The weights of root and siblings classifiers can be stored in separate files to use them for the application to an unseen database.

During the application of this trained network, the test pattern is first presented to the root node classifier which classifies it into one of the main classes. Then the same pattern is applied to the respective class-sibling classifier to classify it to a sub-class type. The root and the sibling classifiers are configured depending on the input size and the number of classes to be discriminated at each level. This network, as a whole, is a *supervised* network, which means, the network is trained according to the desired response of the researcher.

The whole training set was presented to the root node to classify only four main spectral classes and then the respective subset of training set was presented to each sibling network to further classify it into sub-class types. This tree network can be expanded further to discriminate many sub-class types, if the database of any application provides the patterns of those many sub-class types. One advantage of the MTN over a single MBPN for the whole database is that it requires lesser training time, because after the initial training for a few main classes at root node, it requires only partial database for further training at sibling nodes to discriminate the sub-class types.

3. RESULTS AND DISCUSSION

The classification schemes, ANN and $\bar{\chi}^2$, were compared with the catalog classification (as cataloged in Heck et. al., (1984)) and amongst themselves by computing the linear correlation from the scatter plots, their coefficients, standard deviations, etc. Figure 2a shows the scatter plot for ANN vs. catalog. Figure 2b shows a 3D plot of classification errors in luminosity and spectral type on x- and y- axes and the percentage of total test sample along the z-axis. The scatter plot shows that there is, in general, a good correlation between the catalog and ANN classification barring a few points lying outside 3- σ .

An ideal classification, obviously, means that there should be a 45° diagonal line in the scatter plots and any deviation from such a line can be considered as an error in the units of the 4-digit code. Table 1 gives the performance of classification obtained by various schemes. The best performance gives an error of about one- spectral subtype (106 units) after rejecting the points which lie outside 3- σ on the scatter plot.

Comments on the correlation plots and histograms :

- (1) The 75 spectro-luminosity classes chosen do not cover all possible spectral types between O to F type stars and hence the reference set of spectra used for the training is incomplete. The discrete gaps seen in the scatter plots are due to this discrepancy.
- (2) The scatter plots show that most of the stars fall close to the ideal diagonal line suggesting that the schemes reproduce the catalog classification quite satisfactorily with no stars being grossly mis-classified.
- (3) The stars which fall outside 3- σ rejection criterion (~ 5) are the ones which require further in-

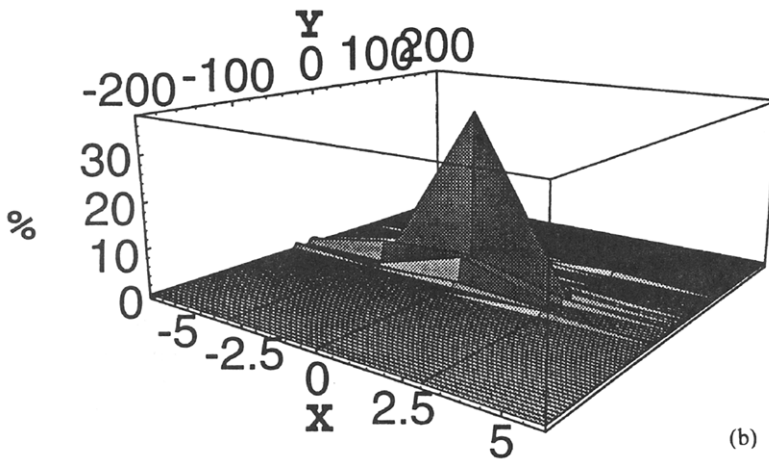
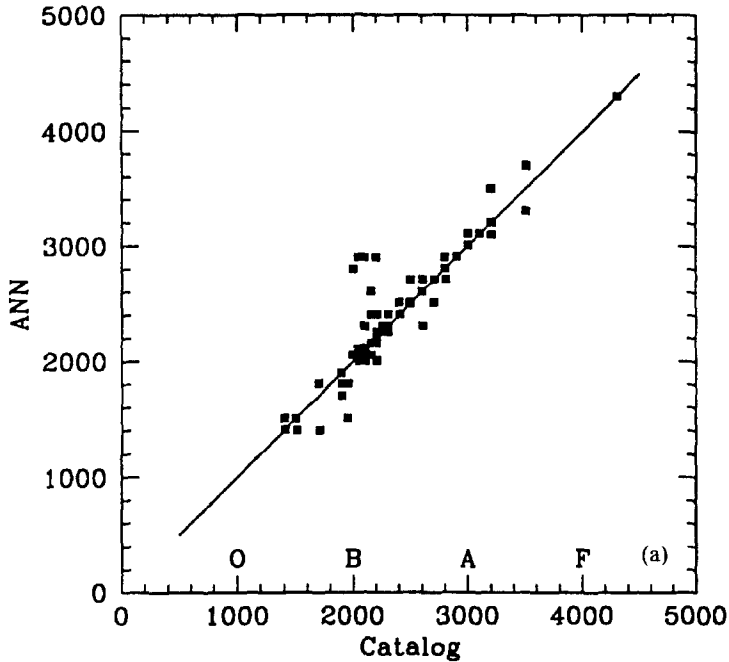


Fig. 2. (a) Scatter plot for ANN vs. catalog. (b) A 3D plot for classification errors in luminosity (x-axis) and spectral type (y-axis) vs. the % of total number of stars (z-axis)

investigation. It is worth mentioning here that these points may be due to the improper training of the ANN, a process which normally involves adjusting several parameters, and some of these are still at an experimental level. On the other hand, it may also be due to the improper selection of continuum and interstellar reddening effects. The aim of this study was to investigate the applicability of ANN on the UV spectra on a rather global manner and the discussion on

such rejected points is really out of the scope of this paper.

- (4) It is seen from Table 1 that the agreement between the ANN and $\bar{\chi}^2$ minimization schemes is much better than that for the cases where either schemes are compared to the catalog classes. This hints at the requirement of reconfirmation of the catalog classification by various human experts !

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