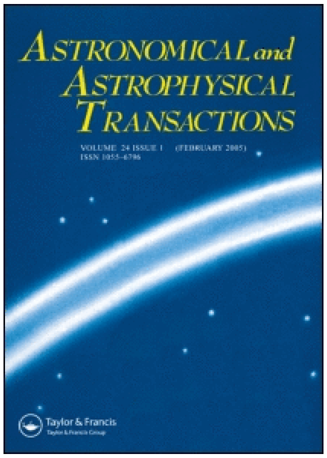

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AUTOMATED DETECTION AND CLASSIFICATION OF OBJECTIVE PRISM STELLAR SPECTRA

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The spectral classification of stars in galaxies is a method of studying their stellar content. In particular, the distribution of spectral types in the stellar systems is a powerful diagnostic for the estimation of their composition, age and evolutionary state. The observational materials mainly used are spectral plates obtained with Schmidt telescopes. Such plates contain, generally, thousands of spectra. There are prism-plate libraries and digitized databases in several astronomical centres that can be fully exploited only with automated processing. Such a system for automated processing of stellar spectra on digitized objective-prism plates is presented. It is developed as a context under the MIDAS environment and provides tools for digital preprocessing of the images (rotating, correcting the tilt, calibration, etc.), for interactive and automated detection of the spectra, for spectra extraction as one-dimensional scans, and finally, for automated classification. Here we particularly present two subsystems of the context, automated detection, applying signal processing techniques to find the beginning of the spectrum, and the automated classification of objective prism stellar spectra, based on a supervised artificial neural network.

KEY WORDS Methods, data analysis, image processing, neural networks – stars, objective prism spectra, classification

1 INTRODUCTION

The analysis of the distribution of spectral types in stellar systems is a powerful diagnostic for the estimation of their composition, age and evolutionary stage. The main observing materials are prism spectral plates taken with Schmidt-class telescopes. Each plate contains thousands of spectra and there are prism-plate libraries and digitized databases in several astronomical centres that can be exploited for this analysis. In order to deal with and to fully exploit the rich pool of spectral data, highly automated image processing and analysis tools need to be developed.

In extracting the physical quantities from the digitized spectral plates there are three main stages: the detection of the beginnings of spectra, their image extraction and, finally, classification of the spectra. The purpose of this paper is to present:

(1) a new, automated method for the detection of spectra, and

(2) an artificial neural network based system for automated spectral classification.

The detection method has been developed as part of the prism plate image processing context OBJPR (Pasian *et al.*, 1997) under the Munich Image Data Analysis System (MIDAS 96NOV, 1996). The detection algorithm, based on signal processing methods, its implementation and some results from the tests of the new method, are given in Section 2. MIDAS as well as the Stuttgart Neural Network Simulator, SNNS v4.1 (Zell *et al.*, 1996) were used to develop the artificial neural network for automated classification. Its architecture, the training process and results from tests are presented in Section 3.

High-quality film copies of IIIa-J plates taken with the 1.2 m UK Schmidt Telescope in Australia have been used for this study. The spectral plates have a dispersion of 830 Å/mm at H_γ and cover the spectral range from 3400 to 5000 Å. The photographic material has been digitized at the Trieste Observatory by means of a PDS 1010 A microdensitometer and at the Royal Observatory of Edinburgh using the Super-COSMOS measuring machine.

2 AUTOMATED DETECTION OF OBJECTIVE PRISM SPECTRA

The automated detection of objects is a common problem in image processing for astronomy and astrophysics. Previous work for automated classification of stellar spectra (von Hippel *et al.*, 1994), for spectral analysis of quasars (Hewett *et al.*, 1995), for galaxy classification (Lahav *et al.*, 1996) or for galaxy redshift measurements (Tucholke and Schuecker, 1992; Schuecker, 1996), applied spectra detection based on already known coordinates of the corresponding stars (either determined for the purpose with the automated plate measuring system or taken from catalogues). Our method is based on processing only the digitized prism plates without the need of the corresponding direct plates and utilizes signal processing techniques (Bratsolis, 1997).

2.1 The Detection Algorithm

The most important feature on which it is possible to rely for spectra detection on an objective prism plate is the beginning of each spectrum, characterized by the presence of intense gradients. Let us consider part of a digitized objective prism plate (Figure 1(a)). This subimage consists of $N \times M$ pixels, and let $I(x, y)$

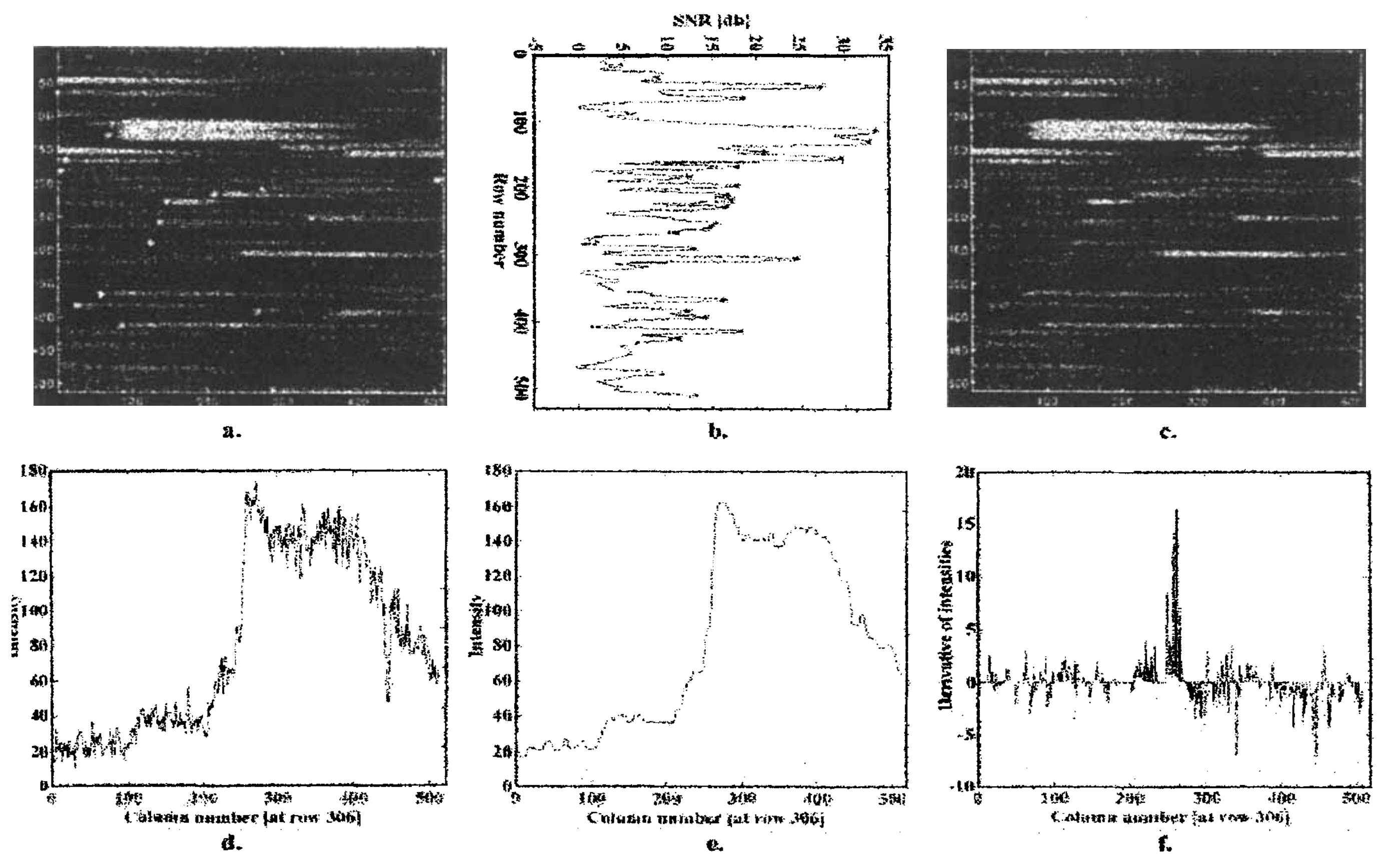

Figure 1 Automated detection of spectra: (*a*) initial image 512 x 512; (*b*) peak picking to separate the stellar spectrum rows from spurious peaks; (*c*) final results of position determination; (*d*) the row 306 as a one-dimensional signal; (*e*) the row 306 after a median and an average filter; (*f*) derivative results of filtered row 306.

denote the value of the pixel (x, y) where the x-axis is down the dispersion. The subimage itself can be considered as a set of M discrete one-dimensional signals $I_y(x) = I(x, y)$. The energy E_y of a particular signal and its variation in decibels SNR_y are defined as:

$$E_y = \sum_{x=1}^{N} I_y^2(x), \quad \mathrm{SNR}_y = 20 \log_{10} \left(\frac{E_y}{\min(E_y)} \right)$$

where the row with the minimum energy $\min(E_y)$ is considered as background. Analysing this variation with an appropriate peak-picking algorithm we can identify energy peaks corresponding to stellar spectrum rows and separate them from spurious peaks (Figure 1(*b*)). The detection of such rows is the first step of the algorithm.

The second step is to fix in each detected row the beginning of the spectrum image. Let us now consider the one-dimensional signal of row 306 (Figure 1(*d*)). In advance we applied to the digitized image appropriate filters resulting in an optimally smoothed spectrum scan (Figure 1(*e*)). Its derivative (Figure 1(*f*)) is used to determine the very beginning of the spectrum, the great change from the background. We find it by fixing the position of the maximal derivative which is leftward of the position of the row's maximum value. This helps us to overcome false detections (absorption and emission features, defects) and to detect only the spectrum beginning, as the crosses on Figure 1(*c*) show.

2.2 Image Sampling

The sizes of the subimage, especially down the wavelength direction, are of crucial importance for the algorithm. In order to avoid missing two spectra on the same row, the subimage should be shorter than the spectrum length. Fixing the subimages length we have to put some restriction on its width in order to take into account the local signal-to-noise ratio that gives better detection limits for the peak-picking process. Both these imply that an image frame should be handled in pieces, subframes.

Taking a subframe from an image, there are often spectra that begin near the subframe's left or right end or are crossed by the bottom or top side. Such spectra probably could not be detected. To avoid this, a partial overlapping of the subframes in both axes should be applied. Having in mind the spectral image parameters, it is optimal to set the subframe sizes to a value of about half of the spectral length, whereas the overlapping size is set to about twice the spectral width.

2.3 The Spectra Detection Procedure DETSP

The above algorithm is implemented in a procedure named DETSP, part of a general context OBJPR (Pasian *et al.*, 1997) for objective prism image processing under MIDAS. The DETSP takes as input an image frame from a digitized spectral plate and particular parameters for the spectra images (dispersion, length, width). The subframes overlapping can be applied to both axes (defaulted), only down the wavelength axis, or skipped altogether. In this way the online plots and/or images displaying (slowing the run) can be switched on/off. The output is a MIDAS format table with the detected spectra positions in world coordinates. It is suitable for use by the procedures of the OBJPR, say for extraction of the detected spectra images. The processing is carried out in four sequential stages:

Image frame preprocessing. The whole image frame is filtered by a sequence of median and smoothing filters. Then, a difference image is created holding the differences between the consecutive pixels of the filtered image down the wavelength axis. Finally, a coordinate grid is determined to fix subframes of the image frame in accordance with the overlapping mode.

Subframe signal processing. Following the fixed grid, all the subframes are sequentially processed by applying the signal detection algorithm to the filtered and to the difference subframes.

Detection table processing. There are possible double detections of spectra near the edges of neighbouring subframes. For this reason, the table of detected spectra is now processed to remove the doubling; it is also sorted.

Fine adjustment of detection. We apply again the signal approach (as in stage subframe signal processing), but only to the detected spectra. Now, a new subframe is considered around the head of the detected spectrum, starting a little before its beginning. The subframe's length is as before, but its width is only a little bigger than the spectral image width. The adjusted position table is finally sorted.

2.4 Results

The DETSP procedure has been developed on a Hewlett-Packard HP C160 workstation (64-bit CPU, 64MB RAM, HP-UX 10.20 operating system) under the MIDAS 96NOV environment. Two frames from digitized high-quality copies of spectral plates taken with the 1.2 UK Schmidt Telescope have been used for tests. One is a 2048×2048 pixel frame from an image scanned by the Super-COSMOS facility at the Royal Observatory of Edinburgh. The other is a frame of 3001×1601 pixels from an image digitized by a PDS1010A microdensitometer at the Trieste Observatory. The DETSP detected 553 spectra on the first frame (Figure 2) and 427 on the second (Figure 3).

In order to test this method, experts detected spectra on these frames using a standard method of detection on direct and spectral plates. The comparison showed that DETSP had missed 13 spectra on the first and 17 on the second frame (errors $< 2.5\%$ and $< 4\%$, respectively). A careful analysis showed that the missed spectra are mainly too faint, so they are unusable for further processing (e.g. automated classification). So, applying the new method, practically all the spectra were automatically detected (true-positive detections $> 96\%$). It is worth pointing out that despite the presence of late M-type and carbon stars on the frames there were no false detections.

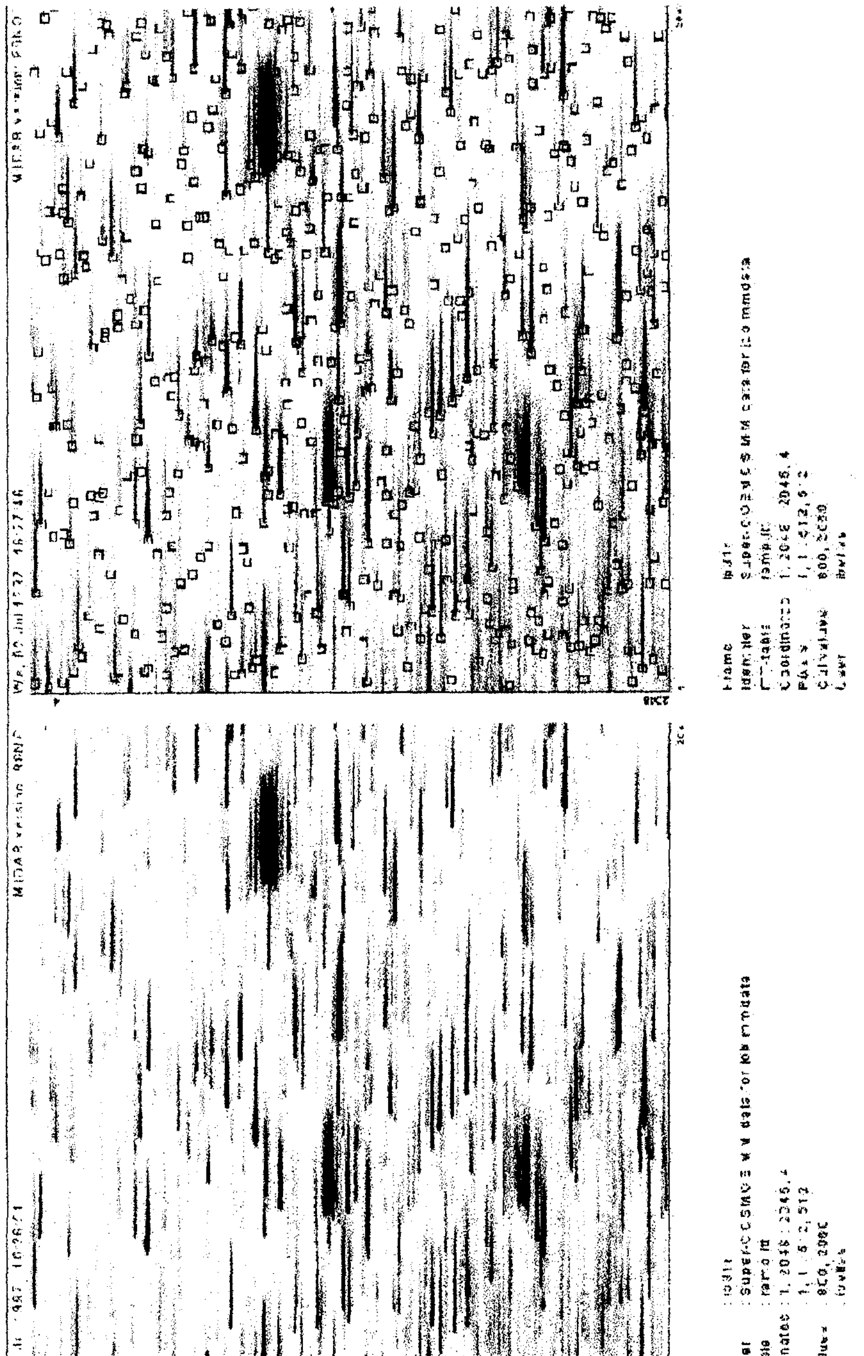

Figure 2 Procedure DETSP test – the 2048 x 2048 pixel frame lp31r.

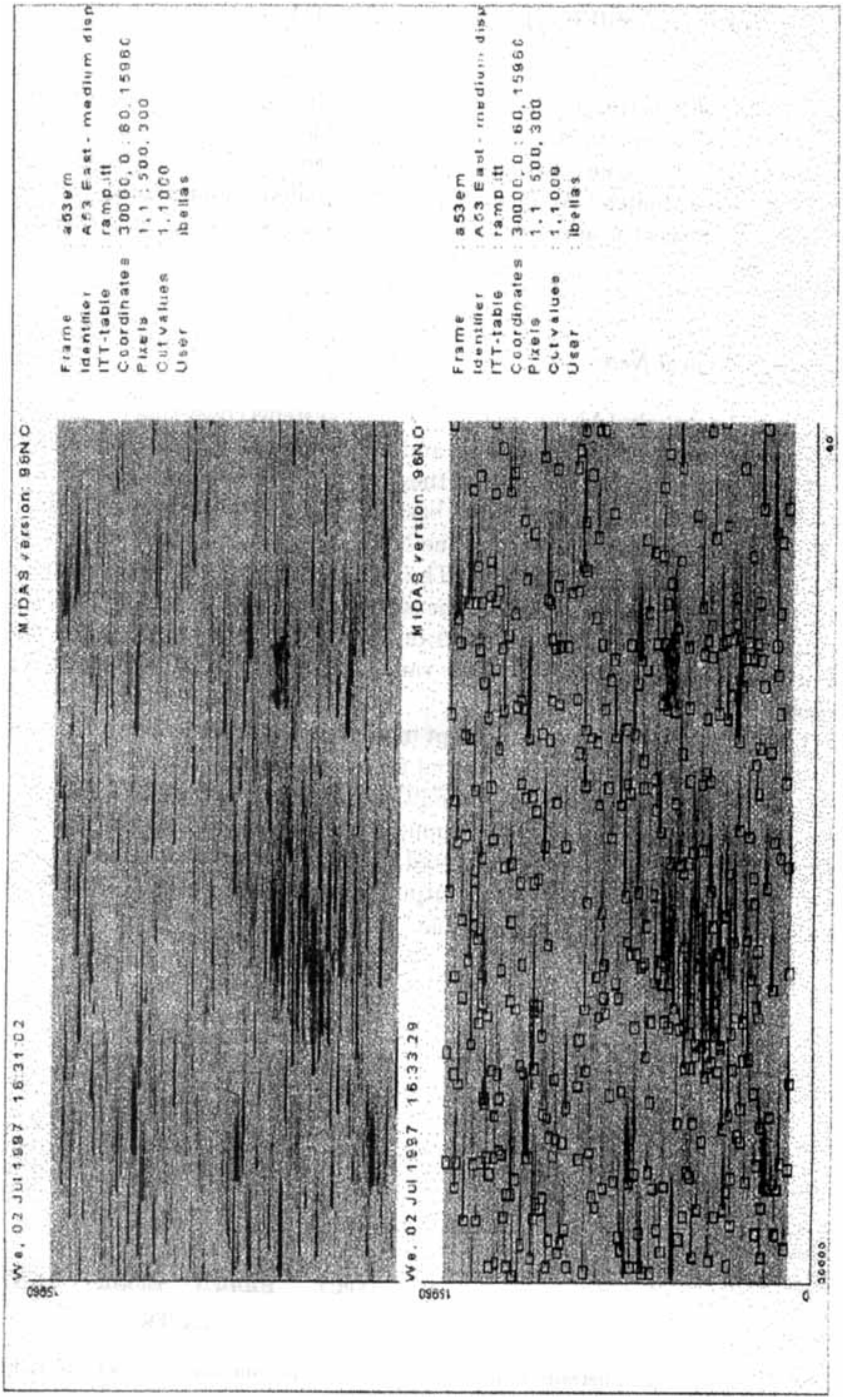

Figure 3 Procedure DETSP test – the 3001 × 1601 pixel frame a53em.

3 AUTOMATED CLASSIFICATION OF OBJECTIVE PRISM SPECTRA

The automation of spectra classification is a difficult task because no clear set of logical rules can be given. In this case, it is preferable to replace the classical logic systems by others with vague conclusions and associative recall – to replace the exact match with the best match. We developed an automated method for classification of objective prism spectra applying such a system, namely a supervised artificial neural network.

3.1 Artificial Neural Networks

Artificial neural networks (ANN) are connectionist systems consisting of many primitive units which are working in parallel and are connected via directed links (Figure 4). The main processing principle of these units is the distribution of activation patterns across the links similarly to the basic mechanism of the human brain. The knowledge is stored in the structure of the links, their topology and weights which are organized by training procedures. The link connecting two units is directed, fixing the source and the target unit. The weight attributed to the link transforms the output of the source unit to an input on the target. Depending on the weight, the transmitted signal can take a value ranging from highly activating to highly forbidding.

The basic function of a unit is to accept inputs from other units acting as sources, to activate itself, and to produce one output that is directed to units – targets. Based on their topology and functionality, the units are arranged in layers. The layers can be generally divided into three types: input, hidden, and output. The input layer consists of units that are directly activated by the input pattern. The output one is made by the units that produce the output pattern of the network. All the other layers are hidden and directly inaccessible.

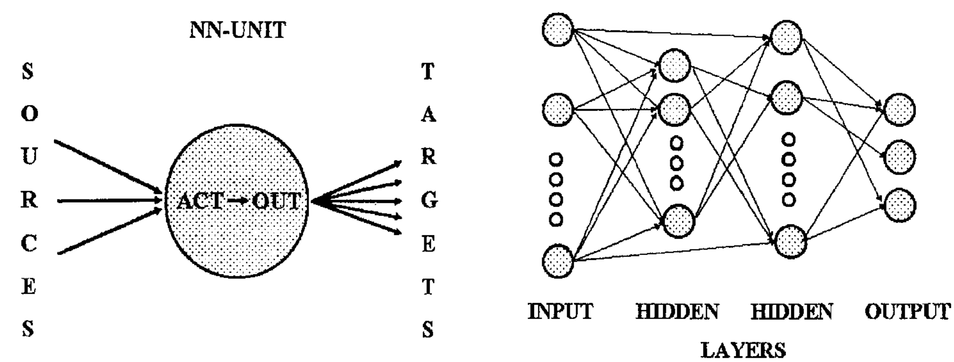

Figure 4 Artificial neural network structure. Left: a unit (neuron) and its functions; right: the ANN layers.

A supervised ANN has to be used for the problem of classification. It must be trained by applying a learning procedure during which the weights are properly adjusted, and there are many different learning algorithms. Choosing the proper one is one of the first steps in developing an ANN. On the other hand, in order to train, verify and to test such a system, sets of input patterns with the corresponding outputs need to be prepared in advance.

The most efficient implementation of ANNs has been achieved by developing special hardware systems (Hecht-Nielsen, 1990). But, the increase in processing power and speed of computer systems gave rise to very effective software simulators of ANNs running on general-purpose computers. One is the freely distributed Stuttgart Neural Network Simulator – SNNS (Zell *et al.*, 1996). It has powerful and flexible tools for developing, training, and testing different ANN architectures and provides a user-friendly graphical interface.

3.2 ANN for Automated Classification of Spectra

The SNNS v4.1 running on a HP C160 workstation has been used to develop the ANN for spectra classification. As it is suggested for classification problems (Zell *et al.*, 1996), we applied the so-called feed-forward architecture with full connection. The links are strictly directed from input toward the output without recursion, and all the elements of a given layer are connected with all the elements of the following layer. An updating mode that follows the network topology and a randomize mode for initialization of the link weights were chosen.

The initial experiments pushed us to the back-propagation learning procedure. For a given input pattern, the output errors, the differences between the real and the desired output pattern, are propagated back to the previous layer (hidden). The weights of the links between the two layers are properly updated in order to minimize the errors. Then, the corresponding differences from the old weights are considered to be errors of the hidden layer and are similarly propagated one layer backward. This continues until the input layer is reached. The learning is repeated for each pattern in the training set. Then the whole cycle is repeated again and again until either a predefined minimum in the error or maximum number of cycles are reached. A modification of this learning mode (with a "momentum term" and experimentally fixed parameters) that leads to better and faster convergence in the error space, was finally used.

The neural network architecture strongly depends on the input and output patterns. A general inspection with MIDAS of the objective prism spectra scans convinced us that there is more than enough to use the initial 256 pixels with starting point a little before the spectrum head (range about 3600–5400 Å). The extracted digitized scans were classified by experts and cover the spectral types from B to M and C (carbon stars). We fixed for output seven spectral types (B, A, F, G, K, M, C) and, additionally, an "unknown". These facts led us to fix the ANN with input layer of 256 units, and the output one of 8 units. For the experiments we used one hidden layer of 64 units (Figure 5). The very

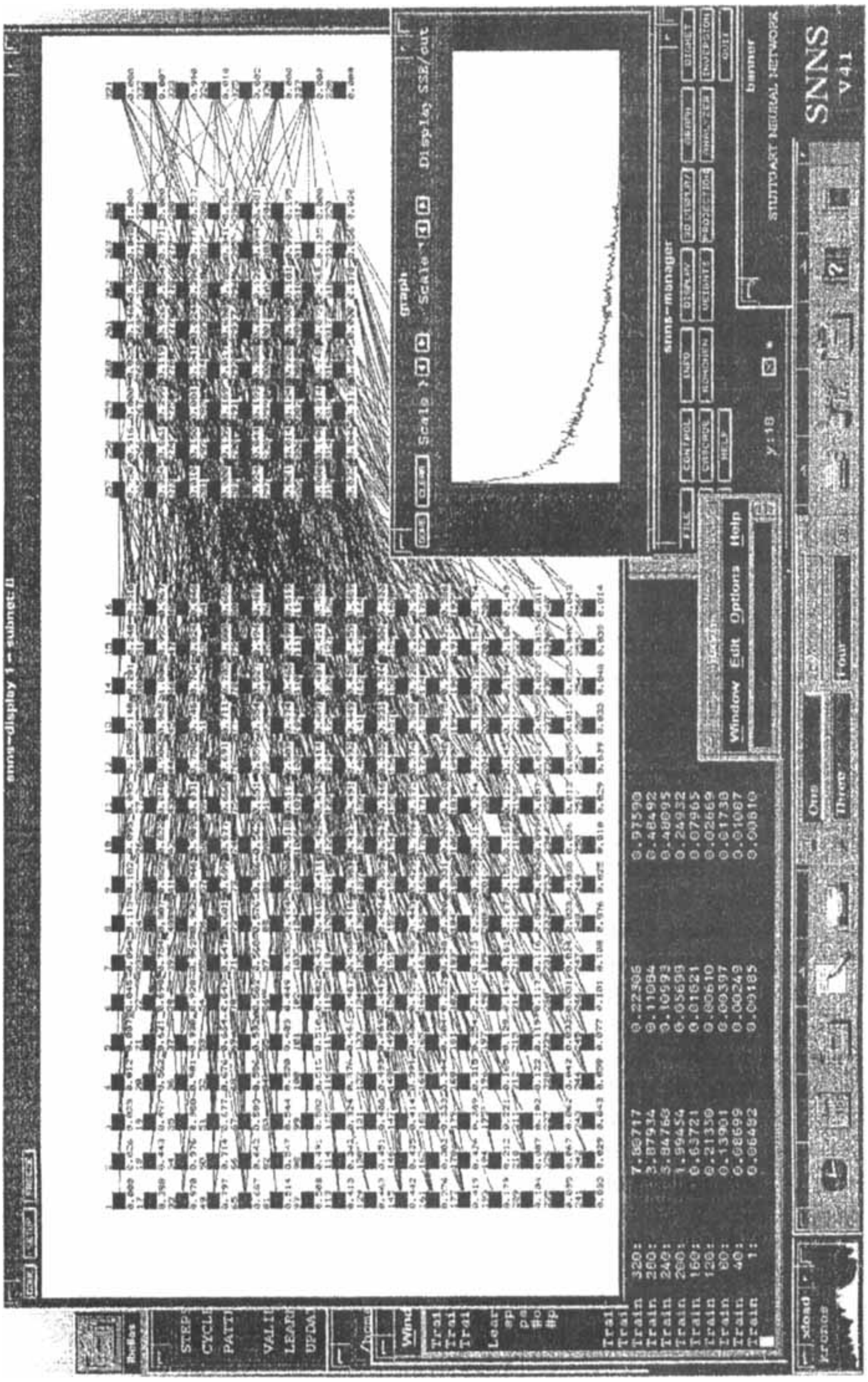

Figure 5 The ANN for spectral classification after training (SNNS). The small plot shows the internal error change during the training.

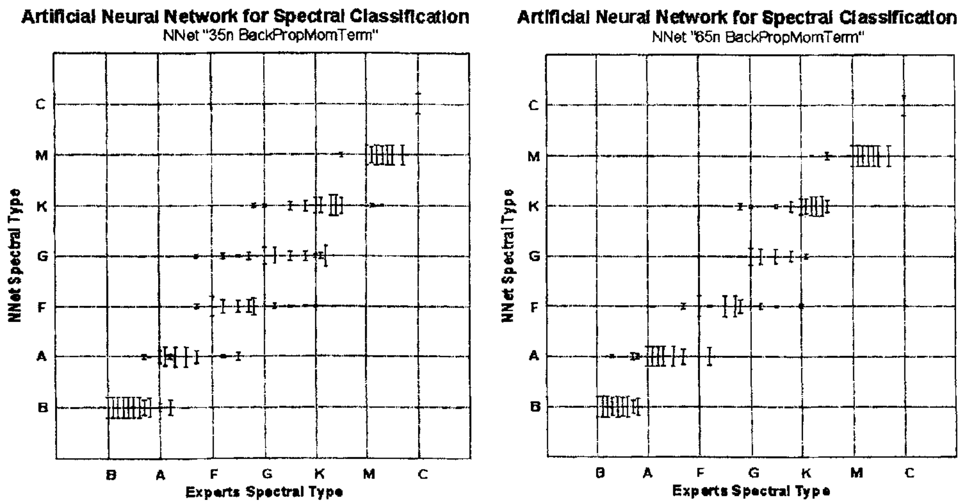

Figure 6 The artificial neural network classifications vs. expert spectral types (the vertical bars show the classification weights). Left: ANN trained with 35 patterns; right: ANN trained with 65 patterns.

first trials showed that by normalizing the scan values we achieved significant improvement of the ANN training. This simple pre-processing was adopted hereafter.

3.3 Experiments and Results Analysis

The experimental database consisted of 140 digitized spectra. After an inspection, two training sets were chosen: a small one of 35 spectra including 5 scans per spectral type and a larger one (65 spectra) with five more scans per type (for B–M stars). Firstly, in order to fix the general parameters and to obtain an estimation of the internal quality of the network architecture we trained the network with the whole input/output pattern set (E140n) of 140 normalized scans. This allowed us to choose the appropriate functions to initialize, update and train the ANN. No more than 400 cycles, taking about 30 seconds (on HP C160), where needed to stabilize the learning at about 0.05 sum squared error per output unit (the output can take a value between 0.0 and 1.0 for spectral type).

Two independent tests were carried out using the two different training sets. All the 140 patterns were used in the verification of the trained ANN. The results from the E065n and E035n tests are summarized in Figure 6. For each input pattern, its spectral type (found by experts) and the ANN-classified (the weight is shown by the vertical bar), are given. In both tests the general properties are about the same, despite the different number of learning patterns. The misclassified objects are stars of either early or late subtypes. In all such cases the weights are small (less than 0.5). There is no misclassification of more than one spectral type with weight greater than 0.2. In a few cases stars were classified as belonging to two types with nearly equal, but very small weights. The analysis of their spectra showed that they are either under- or overexposed.

4 CONCLUDING REMARKS

The procedure DETSP presented in this paper implements a highly efficient algorithm for automated detection of spectra. However, being implemented using the MIDAS command language, it is too slow, exclusively due to an extensive use of disk access. Our next step is to create it as a program in C, runnable by MIDAS, with optimal use of memory.

The experiments with artificial neural networks showed that it can be used successfully for automated spectral classification. The ANN can classify previously unknown spectra with an accuracy of one spectral type. In order to improve the accuracy, a larger training set should be used and maybe a more sophisticated architecture. The SNNS allows us to "output" the trained ANN as a program in C, runnable by a procedure of the OBJPR context under MIDAS.

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