

Hybrid Approach to MK Classification of Stars Neural Networks and Knowledge-based Systems

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Abstract: This paper presents a comparative study of the sensibility of knowledge-based systems and artificial neural networks applied to optical spectroscopy, a specific field of Astrophysics. We propose a description of various neural networks models and the comparison of the results obtained by each technique individually and by a combination of both. Whereas in previous works we developed a knowledge-based system for the automatic analysis of spectra, we shall now use the analysis methods developed in that system to extract the most important spectral features, by training the proposed neural networks with this numeric characterization. We do not only intend to analyse the efficiency of artificial neural networks in classification of stellar spectra; our approach is also focused on the integration of several artificial techniques in a unique hybrid system. The proposed system is capable of applying the most appropriate classification method to each spectrum, which widely opens the research in the field of automatic spectral classification.

Key-Words: Neural Networks, Knowledge-based Systems, Fuzzy Logic, Hybrid Systems, Spectral Features, Classification of Stars

1 Introduction

Stellar spectroscopy is one of the most powerful techniques to study the physical conditions (temperature, pressure, density, etc.) and chemical abundances of stars. In general terms, a stellar spectrum consists of a black body continuum light distribution, distorted by the interstellar absorption and reemission of light and by the presence or absence of absorption and emission lines and molecular bands [1].

Once the spectra of a homogeneous sample of stars have been collected and reduced, the study of the distribution of spectral types and the analysis of spectral data can help to understand the temporary change of the physical conditions of stars from a statistical point of view, and therefore, to learn about their evolution. This is why spectral classification is one of the fundamental aspects of the evolutionary study of stars, and a phase that must be carried out in a fast, efficient and accurate way.

The stellar classification sequence has been for-

malized in a widely adopted, two-dimensional classification system, also known as the Morgan-Keenan system [2], which quantifies stellar temperatures and levels of luminosity. Stars are divided into groups, i.e. spectral types, that are mainly based on the strength of the hydrogen absorption lines and on the presence or absence of some significant lines of Ca, He, Fe and molecular bands.

Due to historical reasons, astronomers classify the temperature of stars in a sequence called OBAFGKM, ranging from the hottest (type O) to the coolest (type M) stars. These spectral types are further subdivided by a decimal system, ranging from 0 (hottest) to 9.5 (coolest). Thus, the coolest type O star ($T=23.000$ K) is called O9.5, whereas the hottest type B star ($T=21.000$ K) is called B0. In addition, a luminosity class that depends on the intrinsic stellar brightness is assigned to the star. Luminosity classes I and II correspond to exceptionally luminous stars or super giants, luminosity classes III and IV to giants

and sub-giants respectively, and luminosity class V to normal dwarf stars, such as our sun (a rather common G6 V star).

The manual classification process is generally based on the use of a reference catalogue of spectral prototypes, classified in the MK system and selected by human experts to be used as a reliable guide in the whole process. In order to compare the stars that are going to be classified with those of the reference catalogue, it is essential to normalise all the spectra and isolate the continuous component (affected by interstellar reddening). Only then the comparison can be focused on the information of the spectral lines. At this point, the standardised spectra must be scaled to make their magnitudes equivalent to the stars of the reference catalogue.

On the basis of the scaled and normalised spectra, experts try to determine the spectral type and the luminosity in the MK System. They measure and study the relation between some absorption lines and the depth of certain relevant molecular bands, and as a result they obtain the first classification of each star [3]. This initial classification is refined by superposing the unclassified spectra and those of the reference catalogue that correspond to the same spectral type, until the spectral subtype is finally determined.

Fig. 1 shows the last phase of a manual classification process. The black line represents the spectrum that is being classified, whereas the discontinuous line represents the spectrum of the reference standard star of the same spectral type.

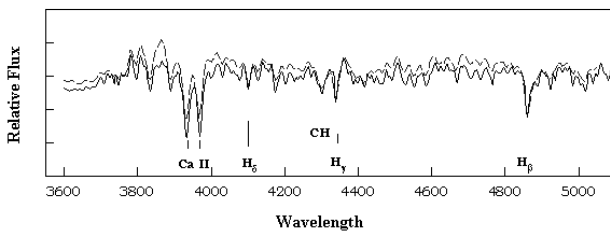


Figure 1: Manual Classification Process

As part of an on-going project devoted to the study of the last phases of stellar evolution, we have collected a sample of approximately 400 stellar spectra from astronomical observations carried out at several telescopes. In order to extract useful information from the individual spectra and to study the evolution of the whole sample, we must complete a solid and systematic spectral classification process.

The manual classification technique described above is often rather subjective and not viable, especially so when the number of spectra is very high and a large number of human resources is required.

It would therefore be advisable to optimise the procedure by means of an automatic, fast and efficient computational technique that assists experts in spectral classifications.

Among the existing techniques of artificial intelligence, knowledge-based systems (KBS) and artificial neural networks (ANN) seem to be most appropriate to approach the problem of stellar classification. Knowledge-based systems can reproduce the reasoning of experts in the field to classify spectra; neural networks, capable of learning the intrinsic relations of the patterns which with they were trained, have already proven their efficiency in classification problems [4] [5].

In previous works, we have presented a knowledge-based system for the classification of the stellar spectra of Post-AGB stars in the visible electromagnetic spectral range [6]. The obtained results led us to extend this system to stars of different luminosities and to add new computational techniques, such as fuzzy logic, in order to refine the automatic classification process.

This article presents several models of neural networks that were designed and implemented to classify spectra. Some well-known previous works have also applied this artificial intelligence technique to stellar classification [7] [8], obtaining diverse resolution grades in the classification. Our intention is not to test models that have already demonstrated their suitability, but rather to implement various neural networks models and as such carry out a sensibility analysis of this technique in the classification of spectra; this will eventually allow us to determine the best learning algorithm and network structure for this specific problem.

Having tested both techniques (KBS and ANN), we can analyse their respective adaptation to the problem and compare their results. Our study combines signal processing [9], knowledge-based systems [10], fuzzy logic techniques [11] and artificial neural networks [12], integrating them by means of a relational database which stores and structures all the classification information and thus provides us with an easy and fast way to compare and contrast the results of the different methods.

The final purpose of this comparative study is the formalisation of a hybrid system that integrates all the abovementioned artificial techniques and is therefore able to determine the most appropriate classification method for each spectrum type. A system that combines knowledge-based systems, fuzzy logic and neural networks is more versatile than a system based on one technique only, and it presents a greater adaptation capability to the problem of stars classification.

The following sections start by describing the

methods and techniques that were used in the developed knowledge-based systems: their algorithms are applied to obtain a numeric parameterisation of the spectra, which is subsequently used in the input layer of most of the proposed neural networks models. Secondly, we describe the different sets that were chosen for the training of the networks, and all the pre-processing stages that are applied to the data before they are presented to the networks. Thirdly, we describe the different neural models that were tested, and we contrast their results. Finally, we propose a hybrid solution that combines both artificial techniques.

2 First Approach: Knowledge-based Systems

As mentioned in Sect. 1, our previous works proposed the design and implementation of an automatic classification system that provides the user with a comfortable tool for the processing of spectra of luminosity I, III and V -stars. That first approach integrated signal processing, knowledge-based and fuzzy techniques, obtaining a very satisfactory emulation of the current manual process. Our final system was able to classify stars with a success rate very similar to the agreement percentage between experts in the field (about 80%), and allowed two classification modalities: spectra with no given luminosity class, and spectra of stars with a well-known luminosity level.

This paper does not describe the developed system in detail, since a more complete description can be found in [13]. We only include a brief explanation of the different modules so as to clarify how the spectral parameters are obtained and measured.

2.1 System Description

The developed system includes two different tools: a spectral analyser and a stellar classifier.

The spectral analyser makes an exhaustive morphological analysis (calculation of maxima, minima, energy, etc.) of the spectra in order to obtain a numerical parameterisation. The parameters are the absorption/emission lines and the molecular bands; we consider 10 bands, 9 lines, and the relevant relationships between them. The spectral analyser is equipped with signal processing techniques to extract and measure the main spectral features of each spectrum. It is developed in C++ [14] and integrates ad hoc ActiveX components for the visualisation of spectra.

The analyser retrieves the spectral data from a relational database that stores and structures the information from human and bibliographic sources [15]. The stellar database is implemented by means of the

PostgreSQL Database Management System running under Linux [16]. At present, approximately 500 spectra of our survey are stored in the database, and they will soon be available via the Internet.

The stellar classifier is based on the development of three different knowledge-based systems that combine traditional production rules with credibility factors [10] and fuzzy logic [11], in order to manage the uncertainty and imprecision that characterise human reasoning in this field. The developed knowledge-based systems use the parameterisation of the spectral analyser to reason and reach a conclusion about the spectral type and luminosity of each star. We applied the Shortliffe and Buchanan methodology [10] to carry out an evolution with fuzzy sets and membership functions that are contextualised for each spectral type. We extracted and measured the classification parameters in the spectra of the guide catalogues (Silva [17], Pickels [18] and Jacoby catalogues [19]) by means of the spectral analyser. This allowed us to define as many fuzzy variables as classification levels (global, type and subtype) for each luminosity level, as well as the different fuzzy sets and membership functions determined by the values of the spectral features in the spectra from the reference catalogue. The classifier was developed in OPS/R2 [20] and integrated with the analyser by means of dynamic link libraries (DLL).

Before entering the second approach, i.e. neural networks, we shall describe in detail the algorithms designed to extract and measure the spectral parameters that are used as the input layer of most of the proposed neural networks models.

2.2 Morphological Algorithms

From a morphological point of view, an absorption line is a descending (ascending for emission) deep peak that appears in an established wavelength zone [3]. To accurately calculate the intensity of each line, we carry out an estimation of the local spectral continuum. We smoothen the signal with a low pass filter, excluding the peaks in an interval around the sample where the line was detected. This filter is implemented by a five-point moving average method that selects the five more stable fluxes. That is

$$C_j = \left(\frac{\sum_{j-n}^{j+n} E_i * X_i}{N} \right), \quad (1)$$

where C_j is the estimation of the continuum for sample j , E_i is the flux in sample i , N is the number of values used in the moving average method to calculate the local spectral continuum, and X is a binary vector that indicates the representative fluxes of the spectral

continuum in the zone. This means that $X_i = 1$ if E_i is a flux value representative of the local spectral continuum, and $X_i = 0$ if E_i is a peak. The intensity is positive for the absorption lines and negative for the emission lines.

A molecular band is a spectral zone where the flux suddenly decreases from the local continuum during a wide lambda interval [3]. For the molecular bands this means that we only have to measure their energy to decide if they are significant enough. In this case, the upper threshold line for each band is calculated by means of linear interpolation between the fluxes in the limits of the interval defined for each band. Then, the area between this line and the axis of abscissas is calculated with discrete integral; the area that surrounds each band is calculated by integrating the flux signal between the extremes of the band. Finally, the flux of the band is obtained by subtracting both calculated energies. That is

$$B_{lr} = \int_l^r L(\lambda_i) - \int_l^r E(\lambda_i) , \quad (2)$$

where B_{lr} is the flux of the band between the samples l and r , L is the projection line, E is the flux function, λ the wavelength, l the left limit of the band and r the right limit. Since the obtained value becomes more negative as the band becomes deeper and wider, positive or negative values close to zero are not considered as bands.

We have also elaborated other algorithms to estimate the flux of some additional spectral features that are not directly considered in the manual process, such as spectral energy. We have examined the spectra classification capacity of these features.

2.3 Enhanced Knowledge-based Systems

An additional research consisted in improving the developed knowledge-based systems by applying the results of the best neural models, which shall be described in the next section. The weights of the output layer units were analysed so as to determine, for each spectral type, which input parameters have more influence on the output. The normalised values of the higher weights were included in the knowledge-based systems, implemented for stars of luminosity I, III and V, in the shape of credibility factors of the rules that correspond to the most influential parameters for each spectral type.

Table 1 compares the performances of the enhanced version of the knowledge-based systems and the original version described above. These results proceed from the performance evaluation of a set of 100 spectra. On the basis of this comparison, we can

affirm that the modification of the reasoning rules (using the weights values of the trained neural networks) has resulted in a slightly significant improvement of the performance of the original knowledge-based systems (around 2%).

Table 1: Performance for Original and Enhanced KBS

Spectral Types	Original KBS	Enhanced KBS
B0-A9	84.3%	87.5%
F0-G9	91.8%	93.2%
K0-M7	95.5%	96.7%

3 Second Approach: Artificial Neural Networks

We have chosen a complete and consistent set of spectra in order to design and test the neural networks that will be applied to the problem of stellar classification. The selected spectra proceed from three different catalogues, which were previously used for the design and implementation of the knowledge-based systems' reasoning rules. This strategy has allowed us to compare the results of both techniques.

We consider 285 spectra that belong to the catalogues of Silva [17] (42 spectra sampled in the range of 3500 to 8900 Å with 5 Å of spectral resolution), Pickels [18] (115 spectra sampled in the range of 1150 to 25000 Å with 5 Å of spectral resolution) and Jacoby [19] (128 spectra sampled in the range of 3510 to 7426 Å with 1.4 Å of spectral resolution). These spectra cover all the types and luminosities described in Sect. 1 and are sufficiently representative, because they offer a continuous transition of the spectral features between each spectral type and its adjacent types.

The training set consists of approximately 50% of the spectra of each spectral type, leaving around 15% of them to validate the learning, and the remaining 35% to test the networks. Table 2 shows the distribution of the sets of spectra that were chosen to design the networks.

The training, validation and testing patterns that are presented to the neural networks were obtained automatically by adding the necessary functions to the spectral analyser developed in the knowledge-based systems approach.

These patterns include the measurement of 25 spectral features (absorption and emission lines, molecular bands, relationships between lines and spectral energy) [3] that are extracted and measured by the algorithms described in Sect. 2.2. We do not

Table 2: Composition of the Three Spectra Datasets

	B	A	F	G	K	M	Total
Train. Set	32	27	27	27	18	14	145
Valid. Set	6	7	6	7	8	6	40
Test Set	21	16	15	15	16	17	100
Total	59	50	48	49	42	37	285

make a previous selection of the parameters that concern each spectral type. As a result, the input layer of the neural models proposed includes 25 neurons, one for each parameter, and an extra neuron (teaching input) in the case of supervised learning.

Before calculating the value of the 25 spectral parameters for the construction of the different pattern sets, the spectra of the three catalogues were scaled to flux 100 at wavelength 5450 Å in order to normalise the flux values and adapt them to the guiding catalogues values. The catalogues we used cover various spectral ranges, since we are not interested in the full spectra, only in the spectral range where the spectral parameters are located, i.e. from 3900 Å to 7150 Å. The sampling frequency is not decisive and it can therefore be different for each catalogue: the analyser looks for the lines and bands in a fixed spectral zone and includes an algorithm to calculate the catalogue resolution.

Once the input values are obtained by the spectral analyser, they must be normalised so as to be presented to the neural networks. Our study standardises the inputs of the networks in two different ways:

1. Global normalisation: a global sigmoidal function is applied to all the parameters. This function normalises the input parameters in the [0, 1] interval. That is

$$1 / (1 + e^{-x}) \quad (3)$$

2. Contextualised normalisation: a specific sigmoidal function is applied to each parameter, that is

$$1 / (1 + e^{-(a*x+b)}) \text{ with } a > 0 \quad (4)$$

This function normalises the input parameters in the [0, 1] interval and centers and scales the distribution function of each parameter properly. The constants a and b were obtained by choosing a minimum (X_1) and a maximum (X_2) for each parameter, so that 95% of the parameter values

are found between them. Thus, solving the following system of equations, the values of a and b are determined for each spectral parameter, depending on the chosen minimum and maximum.

$$0.025 = 1 / (1 + e^{-(a*x_1+b)})$$

$$0.975 = 1 / (1 + e^{-(a*x_2+b)})$$

The neural networks of the experiment correspond to the general types Feed-forward, Self-Organizing Maps (SOM) and Autoassociative Networks. In particular, we have implemented Back-propagation networks, Kohonen networks and Hopfield networks. In the first phase of the experimentation, we have studied the capacity of these three neural models to differentiate between the spectral types A-B, F-G and K-M separately. This previous study has helped us to determine the best network for each pair of consecutive spectral types (B-A, F-G, K-M). The topologies, the learning functions and the results obtained by these networks are described below.

3.1 Feed-forward Networks

The feed-forward model is based on two learning stages: forward propagation and backward propagation. Training a feed-forward neural network with supervised learning consists of presenting a set of input patterns that will be propagated forward by the network until activation reaches the output layer. This constitutes the so-called forward propagation phase. When the activation reaches the output layer, the output is compared with the teaching input (provided in the input patterns). The error, or difference δ_j between the output o_j and the teaching input t_i of a target output unit j , is then used together with the output o_i of the source unit i to compute the necessary changes of the link w_{ij} . Since the errors are propagated backwards, this phase is called backward propagation [12].

Most neural networks that currently function as described are backpropagation networks. In our first experiments, we have made use of three different backpropagation learning algorithms: Standard backpropagation, Enhanced backpropagation and Batch backpropagation.

We have tested the three backpropagation learning algorithms for the spectral types A-B, F-G and K-M; we have tested them through the use of the two implemented normalisation processes; and we have trained various backpropagation networks with and without the validation set.

As for the topology of the networks, the different implemented networks are shown in Table 3. These

topologies were also tested for the three backpropagation learning algorithms.

Table 3: Topologies for Backpropagation ANNs

N°	Hidden Layers	Hidden Units	Output Units
1		3	1
1		3	2
1		5	1
1		5	2
3		10, 5, 3	1
3		10, 5, 3	2

In the training phase, the topological order was used to update the weights: firstly the weights of units in the input layer were updated, then the units in the hidden layers, and finally the units in the output layer. The weights were initiated randomly with values in the [-1, 1] interval. The number of training cycles, the frequency of validation and the values of the learning parameters (η , *momentum* and *flat*) were changed during the learning phase of the different implemented topologies.

We used the Stuttgart Neural Network Simulator [21] (SNNS v.4.1) to implement the above described networks and also to transform them to C code in order to integrate the networks into the developed classification system. This simulator includes parameters that evaluate the training process of backpropagation networks: Mean Square Error (MSE) and Sum Square Error (SSE). Our observations show that the implemented networks converge when the MSE is equal or inferior to 0.05, which is when the network becomes stable. If the training continues after having reached this MSE rate, the network is overtrained and its performance decreases. In this simulator, an output greater than 0.5 is equivalent to 1, otherwise to 0. In the analysis of the results, outputs near 0.5 were not considered successful (from 0.45 to 0.55).

3.2 Self-Organising Maps

The Self-Organising Map algorithm of Kohonen is based on unsupervised learning. SOMs are a unique type of neural networks, since they construct topology-preserving mappings of the training data where the location of a unit carries semantic information [22]. Self-Organising maps consist of two layers: a one-dimensional input layer and a two-dimensional competitive layer, organised as a 2D grid of units. Each unit in the competitive layer holds a weight vector, W_i , which, after training, resembles a different input pattern. The learning algorithm for the SOM networks accomplishes two important objectives: the

clustering of the input data, and the spatial ordering of the map which makes similar input patterns tend to produce a response in units that are close to each other in the grid. In the learning process, the input pattern vectors are presented to all the competitive units in parallel, and the best matching unit is chosen as a winner.

We have tested various SOM networks for the spectral types A-B, F-G and K-M, using the two implemented normalisation processes. The Kohonen networks do not use validation during the training, so the validation spectra were applied to train the network in addition to the training set. In this neural model, we have added one spectral type to each couple of spectral types (B-A, F-G and K-M) in order to let the network perform the clustering easily. This additional spectral type was chosen to be as different as possible from each couple of spectral types, i.e. we have chosen type M for the nets of B-A and type B for the nets of F-G and K-M.

The input patterns are again formed by the 25 spectral features, one for each unit in the input layer. We have increased the number of units of the competitive layer from 2 to 12.

The number of training cycles and the values of the learning parameters ($h(t)$, $r(t)$, *decreasefactorforh(t)* and *decreasefactorforr(t)*) were changed during the learning phase of the different implemented topologies.

3.3 Autoassociative Networks

The autoassociative networks store single instances of items, and can be compared to human memory. In these networks, each pattern presented to the network serves as both the input and the output pattern. Autoassociative networks typically consist of a single layer of nodes, with each node representing some feature of the environment. They use the Hebbian learning [12] as learning function. In this kind of learning, weights between learning nodes are adjusted so that each weight better represents the relationship between the nodes. Nodes that tend to be positive or negative at the same time will have strong positive weights, whereas those that tend to be opposite will have strong negative weights. Nodes that are uncorrelated will have weights near zero.

We have designed an autoassociative network with 26 input units (one for each spectral feature and an extra unit for the teaching input). The network was tested with both implemented normalisation processes.

In the training phase, we used the synchronous order to update the weights. The number of training

cycles and the values of the learning parameters (n) were changed during the learning phase.

The SSE parameter was used to evaluate the network performance, considering the same thresholds as in backpropagation networks.

3.4 ANN Models for Complete Classification

After having tested three kinds of network models for all the spectral types (Backpropagation, Kohonen and Hopfield networks), we have selected the best network of each class in order to compare the results and decide which is most suitable for the classification of each spectral type. The characteristics and topology of the networks with a higher performance are described below. These three neural networks have been tested by using the 100 spectra from the test set in order to evaluate which is the best network for each spectral type. Considering the results, we may conclude that the best network for classifying spectral types from B0 to A9 is the described backpropagation, as well as for types from F0 to G9. However, the Hopfield network obtained a slightly higher success rate for spectral types from K0 to M7. These two neural models produced a similar performance rate, whereas Kohonen networks obtained a lower performance (around 75% in the best cases). This could be due to the size of the training set: since these kinds of networks are not supervised during training and have to cluster the data by themselves, they need a training set that is big enough to extract similarities and group the data.

Once we have determined the best network for each couple of spectral types, we can propose neural models to accomplish the whole process of temperature classification. The basic networks for these models are the neural nets described in previous sections.

We propose two neural models to classify all the spectral types at the same time:

1. Network of neural networks: we implemented a structure of various neural networks based on the best networks for each type.

The first level consists of a backpropagation network that determines the global type of each spectrum, i.e. early star (B, A), intermediate star (F, G) or late star (K, M). This network presents 26 neurons in the input layer, 6 neurons in the hidden layer and 3 neurons in the output layer (one for each global type) and it has been trained with the described training and validation sets.

The second level was built with the best neural networks that were obtained for each couple of spectral types: the chosen backpropagation network for types B, A, F, G and the chosen Hop-

field network for types K and M. The first backpropagation network decides which network the spectra are sent to; sometimes the spectra are sent to two different networks of the second level, especially those that are in the threshold of a spectral type, for example B9A0.

The final trained networks of this model were implemented in C++, which allows the spectra to be sent from the first to the second level. The conceptual design of this network is shown in Fig. 2.

2. Global backpropagation network: we have also tested a global backpropagation network that classifies spectra of all the spectral types simultaneously.

This network presents an input layer of 26 units, with 8 neurons in the hidden layer and 6 units in the output layer (one for each spectral type that is of interest). The network was trained and tested with the same set of spectra as the previous model, which guarantees a consistent comparison between them.

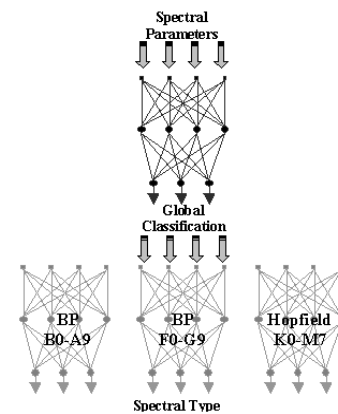


Figure 2: Model of the Net of Neural Networks for Complete Classification

Fig. 3 shows the global performance and the results for each spectral type of the two models proposed for full spectral classification of stars.

In view of the results, we consider that the first approach is more suitable for the spectral classification problem, since it can classify stars of all spectral types with a success rate of 95.4%, as opposed to the 82% obtained by the global backpropagation network.

4 Final Results

The previous sections proposed several methods and techniques to approach the problem of stellar classification. After having used two global artificial intelligence techniques, knowledge-based systems and

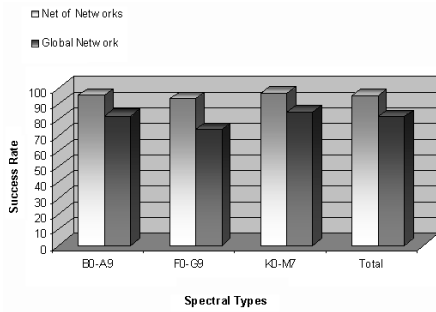


Figure 3: Results of the ANN Models proposed for Temperature Classification

artificial neural networks, we can now make a final comparison between them.

We have selected the neural model with the best performance (net of neural networks) and we have analysed and classified, by means of knowledge-based systems, the spectra that were used to test this network (100 spectra). Since the neural network was trained with the spectra used as reference catalogues in the knowledge-based systems, a proper comparison is possible.

Table 4 contrasts the behaviour of the two artificial techniques and that of two human experts who collaborated on this project. In the neural networks, we considered the ambiguous classifications (outputs in [0.45, 0.55]) as an error, and in the knowledge-based systems we do the same for classifications with a low probability (lower than 75%).

Table 4: Final Comparison between KBS and ANN

Approach	Global	Spect. Type	Lum.
Human Exp. A	99.0%	92.0%	81.0%
Human Exp. B	95.0%	85.0%	70.0%
KBS	98.6%	90.3%	78.2%
ANN	97.0%	95.4%	81.0%

Considering the results, we can conclude that the neural networks approach is very performative in obtaining the spectral types and luminosity of stars, whereas knowledge-based systems present a higher performance in determining the global stellar classification.

After an exhaustive analysis of the performance and results of both artificial techniques (neural networks and knowledge-based systems), we now integrate them in a unique system that guarantees a reliable, consistent and adapted classification of the stars.

Our strategy consists of choosing, among all the

models described in the previous sections, those methods that present the best performance for each classification level. This hybrid system is mainly based on a knowledge-based system that determines the global type of each star and that, according to the type, sends the spectra to different neural networks in order to obtain their spectral type as well as their luminosity level. The hybrid system can determine the most advisable classification method for each different spectrum type, achieving thus more versatility and adaptation than a classification system that uses only one technique.

5 Conclusions

This paper has presented an exhaustive analysis of the capability of knowledge-based systems and artificial neural networks to classify the spectra of stars. We have confirmed that neural networks are more adequate to determine the spectral types and luminosity of stars, whereas knowledge-based systems are best suited to determine the global temperature.

In order to obtain the input patterns of the neural networks, the morphological analysis algorithms developed in the knowledge-based systems were used to extract and measure spectral features. Several networks were trained with this parameterisation, and other networks with flux values of specific spectral zones, but finally the first strategy obtained the best performance.

We have described several models of neural networks and analysed their performance and results to discover the best approach to the classification of each spectral type. In particular, backpropagation networks, self-organising maps and autoassociative networks were designed and tested, and we implemented various topologies in order to obtain the global classification, spectral type and luminosity of stars. The best networks reached a success rate of approximately 97% for a sample of 100 testing spectra.

As an additional study, the developed knowledge-based systems were modified by using the results of the best implemented neural models, which significantly increases the performance of the original systems.

Finally, both artificial techniques were integrated in a hybrid system that determines the most appropriate classification method for each spectrum. This hybrid approach is a versatile and flexible automatic technique for the classification of stellar spectra.

For the evaluation period of the proposed models, we could count on the essential collaboration of experts from the area of Astronomy and Astrophysics of the University of A Coruña.

At present, we are analysing functional networks in order to determine the suitability of this artificial technique in stellar classification. We are also completing the development of our stellar database, STARMIND (<http://starmind.tic.udc.es>), so as to make it accessible through the Internet. Our objective is to enable users worldwide to store and classify their spectra, which will help us to improve the adaptability and accuracy of our automatic analysis and classification system.

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