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STARMIND: A FUZZY LOGIC KNOWLEDGE-BASED SYSTEM FOR THE AUTOMATED CLASSIFICATION OF STARS IN THE MK SYSTEM

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ABSTRACT

Astrophysics is evolving toward a more rational use of costly observational data by intelligently exploiting the large terrestrial and spatial astronomical databases. In this paper, we present a study showing the suitability of an expert system to perform the classification of stellar spectra in the Morgan and Keenan (MK) system. Using the formalism of artificial intelligence for the development of such a system, we propose a rules' base that contains classification criteria and confidence grades, all integrated in an inference engine that emulates human reasoning by means of a hierarchical decision rules tree that also considers the uncertainty factors associated with rules. Our main objective is to illustrate the formulation and development of such a system for an astrophysical classification problem. An extensive spectral database of MK standard spectra has been collected and used as a reference to determine the spectral indexes that are suitable for classification in the MK system. It is shown that by considering 30 spectral indexes and associating them with uncertainty factors, we can find an accurate diagnose in MK types of a particular spectrum. The system was evaluated against the NOAO-INDO-US spectral catalog.

Key words: astronomical databases: miscellaneous – methods: data analysis – stars: fundamental parameters

Online-only material: machine-readable and VO tables

1. INTRODUCTION

A knowledge-based system (KBS) or expert system (ES) can be defined as a computer system that is programmed to imitate human problem solving by means of artificial intelligence (AI) techniques and references to a database of knowledge on a particular subject (Giarratano & Riley 2005; Jackson 1998).

Research into AI has revealed that the addition of heuristics-enabled programs to tackle problems that were otherwise difficult to solve by usual computer science techniques. A classical example of application is the computer chess-playing programs that have been strengthened by including knowledge on good positions or overall strategies rather than relying solely on the computer's ability to calculate variations. Academic examples can be found in meteorology, geophysics, or aerospacial engineering, where ESs have been developed to interpret satellite imagery, forecast the weather, or help take decisions.

The use of AI techniques for the analysis of astronomical data has been relatively frequent since the early nineties. Starting from the two main branches of AI—the symbolic-deductive systems (KBSs) and the so-called inductive or subsymbolic approaches (artificial neural networks (ANNs) or connectionist systems)—we find that the vast majority of authors who have applied AI techniques in the field of computational astrophysics have done so according to the second paradigm, i.e., ANNs, but no significant work can be found related to the application of ES to astronomical data analysis. To our knowledge, this is the first time that such a system is applied to the Morgan and Keenan (MK) classification problem.

In the case of computational astrophysics, and particularly in relation to studies whose purpose is to classify and extract stellar parameters from large surveys of spectroscopic or spectrophotometric databases, most authors have used multilayer neural networks (MLP) with supervised learning algorithms based on the backpropagation of the training error. We can mention the already classical works by von Hippel et al. (1994), Singh et al. (1998), Bailer-Jones et al. (1997), Vieira & Ponz (1998), as well as the more recent works by Gupta et al. (2004), Willemsen et al. (2005), Giridhar et al. (2006), and Bazarghan & Gupta (2008). For a revision of various approaches toward the automated analysis of stellar spectra, including ANNs, see the review by Allende (2004).

Astrophysics is moving toward a more rational use of its costly observational material by means of the intelligent exploitation of large terrestrial and spatial astronomical databases. Nowadays, every single project on astronomical instrumentation includes the creation of data archives and their future exploitation with automatic or pseudo-automatic analysis tools. Several international projects are currently working on management systems for astronomical information based on the joint exploitation of all the available spatial archives and astronomical databases (international virtual observatories initiatives). Our research group is an active member of the Spanish Virtual Observatory (SVO; Solano 2006), which consists of various networked Spanish groups and aims, among other things, at developing applications for the automatic analysis of astronomical data. AI techniques are among the techniques that are being used for these developments.

In the particular case of stellar spectra classification in the MK system, where spectral classes are defined by direct comparison with selected template spectra and where the experience and expertise of the astronomer in classification tasks is completely relevant, we find that the nature of the problem corresponds entirely to the scope of a specific KBS. Moreover, we believe that such a system could also be very useful in the training and formation of stellar spectroscopists.

The MK spectral classification system was proposed by Morgan & Keenan in 1943 with the publication of An Atlas of Stellar Spectra (Morgan et al. 1943), the first astronomical atlas of photographic stellar spectra. The MK system is a powerful tool for the study of stellar populations and it has proved useful for many decades to astronomers who need to infer basic quantitative information from a stellar spectrum and its relation to effective temperature and gravity. A weak point of the system is that, since it is based on the comparison of the spectra with an original set of selected standards, it carries a significant degree of subjectivity. It has also been pointed out that calibrations against stellar atmospheric parameters are incomplete and do not cover the entire H–R diagram; see Gray & Corbally (1994) and Garrison (2002).

Even though spectral synthesis utilities have become a usual tool in the interpretation of an observed spectrum, MK classification continues to be a useful quantitative description for a stellar spectrum. It has to be used with caution, since it was originally proposed for Population I stars, and the rules for the definition of spectral classes were originally formulated in the photographic wavelength range and for spectra with the typical resolution of photographic spectrographs, 2–3 Å pixel^{-1}. The use of the MK classification frame beyond the original limits could lead to erroneous classifications, such as assigning a classification of an A-type star to Population II metal-weak F-type stars. Efforts to extend the MK system beyond the original reference frame have already been initiated by Morgan (1984) and Keenan & Yorks (1985), and in the remarkable classical works of Gray & Garrison (Gray & Garrison 1987, 1989a, 1989b; Gray 1989). For a review, see Rountree (2003).

The main objective of the present paper is to prove the potential of an ES to perform automated classification of spectra. We have placed special emphasis on the description of the system, as we think that this AI technique is still not well known among the astrophysical community. In various previous works, published in computer science journals (Rodríguez et al. 2004, 2008; Dafonte et al. 2005), we have presented a comparative study of ESs, ANNs, and statistical clustering techniques for unattended stellar classification. Some preliminary results on MK classification up to the level of stellar subtypes and including luminosity classes were also published. An improvement of the classification resolution by the use of a more complex system is being validated in order to assure its astrophysical significance. This ongoing study will be presented in a forthcoming paper.

The currently proposed system consists of two modules: a base of knowledge and the inference engine that will be described in detail in the following sections.

In order to feed the system a base of knowledge, we developed a spectral database that contains uniform optical spectra of MK standards, listed in several source papers described in Table 1 (available in full in the electronic version). These spectra originate from both public databases and ad hoc observations that were carried out to complete the subtype coverage.

As a step prior to the design of the expert system, we performed a systematic measurement of the main spectral features, line and band fluxes, and equivalent widths, in order to determine a set of spectral indexes suitable for classification in the MK system. We analyzed the sensitivity of these classification parameters so as to define the different fuzzy sets, variables, and membership functions that complete the classification process. This analysis is described in Section 2. Section 3 describes the details and performance of our ES, STARMIND. Finally, the results on classification are presented and analyzed in Section 4. The system was tested on the NOAO INDO-US stellar spectral catalog by Valdes et al. (2004).

STARMIND was designed to provide the MK-type classification of stars in the classical visible wavelength range. It constitutes the initial system of a more complex hybrid system that will be presented in a subsequent paper. We think that the novelty of the AI technique for its application in astronomical classification problems deserves a detailed explanation, which is the main objective of this paper. STARMIND utility is intended for public access and used via the SVO facility.

Table 1
STARMIND MK Standard's Database

STAR	MK Type	MK Ref.	$T_{\rm eff}$	log g	[Fe/H]
HD 100920	G8	Perkins	4800	2.93	−0.34
HD 101501	G8	Perkins	5538	4.69	0.03
HD 102070	G8	Perkins	4870	2.57	−0.11
HD 102212	M1	Perkins	···	···	···
HD 102224	K0	Perkins	4350	1.15	−0.43

Note. References for MK types and physical parameters are detailed in Section 2.
(This table is available in its entirety in machine-readable and Virtual Observatory (VO) forms in the online journal. A portion is shown here for guidance regarding its form and content.)

2. MK STANDARD SPECTRA DATABASE AND SENSITIVITY INDEXES FOR SPECTRAL CLASSIFICATION

Our first motivation for the application of AI techniques to the analysis of stellar spectra was the automation of the process of stellar spectral classification in a survey of postasymptotic giant branch (AGB) stars by Suárez et al. (2001). A primitive version of STARMIND was developed that focuses on luminosity Class I stars, with a resolution in spectral types limited by the spectral database of templates and based entirely on the available public spectral libraries of Pickles (1985), Silva & Cornell (1982), and Jacoby et al. (1992). This experience allowed us to realize that in order to tackle the problem of MK-automated spectral classification it is essential to dispose of the reference of a spectral database that provides good resolution for all the stellar types and as many luminosity classes as possible. We also noted that the primary standard MK templates, the ones that originally defined the system, were indispensable.

So we prepared a spectra database composed of 361 spectra: 279 items originated from public "online" databases and 82 items from "ad hoc" astronomical observations performed during several campaigns with the 2.5 m Nordic Optical Telescope (NOT) at the El Roque de los Muchachos Astronomical Observatory. The spectral coverage and pixel dispersion were standardized from 3870.0 Å to 6240.0 Å and 2.6 Å pixel^{-1}. The content of this database of MK standard spectra is presented in Table 1, available in full in the electronic version. References for the MK classification of stars in this table originate from the following libraries or papers: Morgan & Keenan (1973), label "MK" in Column (3) of Table 1, Gray & Garrison (1987), label "Gray-a" in Table 1, Gray & Garrison (1989a), label "Gray-b" in Table 1, Gray & Garrison (1989b), label "Gray-c" in Table 1, Keenan & McNeil (1989), label "Perkins" in Table 1, and Garcia (1989), label "Garcia" in Table 1. The physical parameters are mean values obtained from the Simbad Astronomical Database measurement catalog Fe-H, based on the compilation by Cayrel et al. (1997). The distribution of spectral types in the adopted MK templates library is shown in Figure 1. Note the scarcity of O-type standard stars, where spectral peculiarities are usual.

It is well known that the MK system classifies stars in a sequence named O-B-A-F-G-K-M, ranging from the hottest

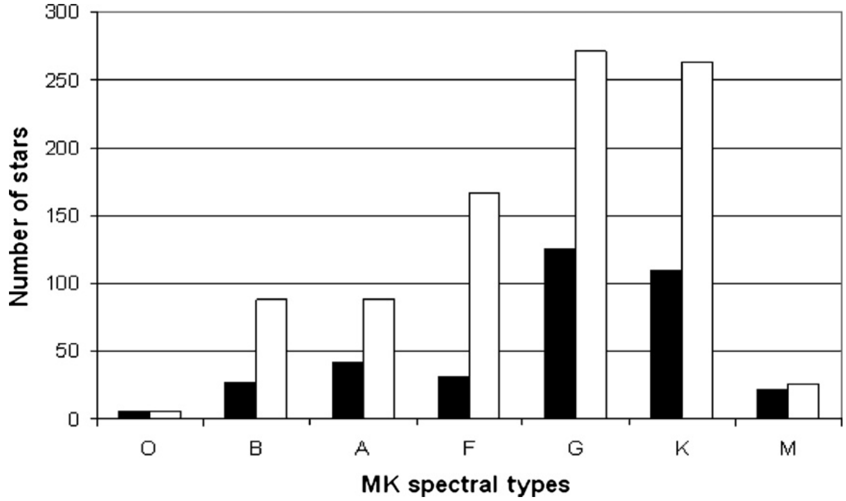

Figure 1. Distribution of MK types in the templates library (black) and in the Coude-INDO-US catalog (white) used for testing the ES.

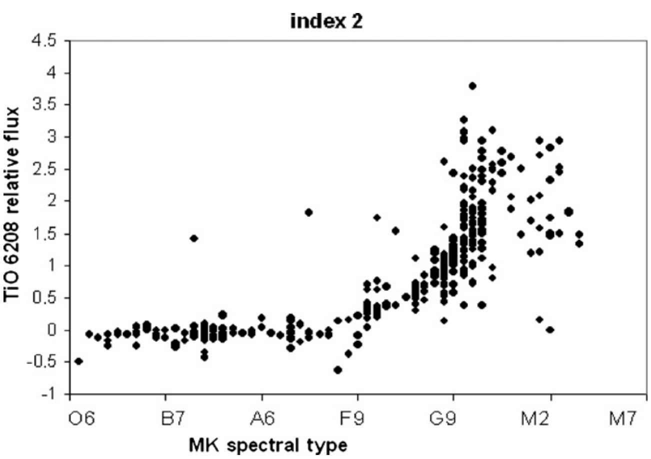

Figure 2. Spectral index for MK classification: TiO band flux at wavelength 6208 Å as a function of the MK type.

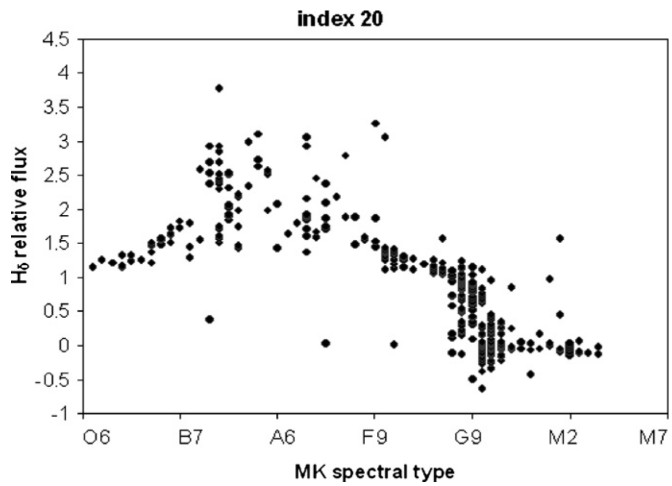

Figure 3. Spectral index for MK classification: Hδ flux as a function of the MK type.

(type O) to the coolest (type M) stars. In addition, a luminosity class is assigned to the star depending on the intrinsic stellar brightness. The original classical rules for the classification of spectra in the MK are based on the strength of the H Balmer lines, the occurrence of He I and He II lines, the relative strength of H and K Ca II lines with respect to H I lines, and the occurrence and strength of metallic lines and molecular bands.

Experts classify spectra on the basis of a visual comparison with the template spectra as defined by the MK system. In order to automatize this process of comparison with standard spectra, the astronomer's knowledge must be compiled in a comprehensive set of morphological features that are to be measured in the spectra. Our own experience, as well as information available in the literature, leads us to consider the following types of morphological measurements of the main spectral features: line and band equivalent widths (EW), absorption lines and bands fluxes, EW ratios, and flux and EW differences. The measurement of these quantities strongly depends on a reliable determination of the local continuum, which is not a straightforward task to automate. We tested several approaches for a nonsupervised determination of the spectral local continuum, and found that the best results were obtained when using an algorithm that detects absorption and emission lines, and adjusts a local continuum in a limited region toward the blue and red of those features. Blue and red continuum regions around each feature were low-pass filtered with a filter that rejects 40% of the points with the higher standard deviation, while the remaining points were interpolated with a polynomial fit to constitute the local continuum.

On the basis of these spectral analyses, a total of 109 morphological measurements were selected for a sensitivity analysis. These features were measured in the spectra of the complete set of 361 MK templates in order to evaluate their suitability to discern among spectral types. Figures 2 and 3 show two of these spectral indexes as a function of MK types. Figure 2 illustrates how the measurement of the flux of a TiO band at 6208 Å (index number 2 in Table 2) gives increasing nonzero values for types later than F9, whereas Figure 3 shows the behavior of the Hδ line (index number 20 in Table 2) as a function of the spectral type. From the original set of morphological features, a total of 64 spectral indexes were found to be well suited to characterize the spectral types. Those indexes are described in Table 2. By applying principal component analysis (PCA) we were able to select a set of 30 spectral indexes, sufficient to perform MK classification in spectral types. These indexes are marked with an asterisk in the first column of Table 2.

Limiting numerical values were determined among large groups of spectral classes (early, intermediate, late, OB, AF, GKM, etc.). We then ranged their performance by determining, among all the spectra that populate a spectral type, the

Table 2
Spectral Indexes Suitable for MK Classification in Spectral Types

ID Number	Index	Carrier
1*	EW 4226	Ca I
2*	Band flux 6208	TiO
3*	EW 4300	Blend TiO-Fe
4*	EW ratio 4226/4101	Ca I, Hδ
5	Band flux 5160	TiO
6*	EW 5270	Fe I
7	Band flux 6154	TiO
8	Band flux 4953	TiO
9	EW 4077	Sr II
10	EW ratio 4300/4340	Blend TiO-Fe, Hγ
11*	EW 4144	He I
12*	Band flux 6134	TiO
13	EW 4455	Ca I
14	Band flux 4946	TiO
15	Band flux 5886	TiO
16*	EW ratio 4226/4481	Ca I, Mg II
17	Band flux 6143	TiO
18	EW ratio 3933/4101	Ca II, Hδ
19	EW ratio 4101/4144	Hδ, He I
20	Line flux 4101	Hδ
21*	EW 4032	Mn I
22*	EW 4026	He I
23	EW ratio 4481/4471	Mg II, He I
24*	Line flux 4861	Hβ
25	EW 3933	Ca II
26	Line flux 4026	He I
27*	Line flux 3968	Hϵ
28	EW 3968	Hϵ
29	Line flux 4144	He I
30*	Line flux 4116	Si II
31*	EW 4173	Fe II
32	EW 4471	He I
33*	EW 4340	Hγ
34*	EW ratio 4226/4101	Ca I, Hδ
35*	EW ratio 4300/4383	Blend TiO-Fe, Fe I
36	Band flux 6182	TiO
37*	EW 5335	Blend Fe I
38	EW ratio 4226/4340	Ca I/ Hγ
39*	Line flux 3933	Ca II
40	EW 4405	Fe I
41*	Line flux 4686	He II
42*	EW 4686	He II
43*	Line flux 4009	He I
44*	EW 4481	Mg II
45	EW 3933- EW 4101	Ca II, Hδ
46*	Line flux difference 3933–4101	Ca II, Hδ
47*	Line flux 4121	He I
48*	EW ratio 4032/4128	Mn I, Si II
49*	Line flux 4405	Fe I
50	Line flux 4455	Ca I
51	Band flux 4295	G Band, CH
52*	EW 4009	He I
53*	Line flux 4226	Ca I
54*	Line flux 4300	Blend TiO-Fe
55	EW ratio 3933/3970	Ca II, Hϵ
56	EW ratio 4045/4173	Fe I, Fe II
57	Line flux 4686	He II
58	EW ratio 4226/4340	Ca I, Hγ
59	EW 4921	He I
60	Line flux 4383 + 4405	Fe I
61	Line flux 4921	He I
62	Line flux 4481	Mg II
63	EW ratio 4226/4481	Ca I, Mg II
64	Line flux 5270	Fe I

Table 3
STARMIND Hierarchical Decision Rules and Compliance Percentages for MK Classification in Spectral Types

Classification Rules	Compliance Percentage	Spectral Indexes Involved
N1.1	⩾95	1–4
N1.2	⩾91	6
N1.3	⩾90	12
N2.1.1	⩾98	21
N2.1.2	⩾90	16, 22, 24
N2.1.3	⩾95	27
N2.2.1	⩾97	11, 33, 34
N2.2.2	⩾96	35
N3.1	⩾93	41, 42, 43
N3.2.1	⩾68	31, 37, 44, 46
N3.2.2	100	30, 39, 47, 48, 49
N3.4.1	⩾90	41, 49, 52, 53, 54

Table 4
Confusion Matrix Between INDO-US and STARMIND MK Types Classification

	O	B	A	F	G	K	M
O	6	0	0	0	0	0	0
B	4	68	15	1	0	0	0
A	0	3	80	7	0	0	0
F	0	0	27	130	8	1	0
G	0	0	16	30	169	56	1
K	0	0	0	0	13	245	3
M	0	0	0	0	0	2	25

Table 5
Confusion Matrix Between INDO-US and STARMIND MK Types Classification[a]

	O	B	A	F	G	K	M
O	6	0	0	0	0	0	0
B	3	83	1	1	0	0	0
A	0	2	82	6	0	0	0
F	0	0	21	140	4	1	0
G	0	0	16	9	212	34	1
K	0	0	0	0	1	257	3
M	0	0	0	0	0	0	27

Note. [a] In this case, discrepancies affecting only 1 subtype are considered correct classifications.

Table 6
Confusion Matrix Between INDO-US and STARMIND MK Types Classification[a]

	O	B	A	F	G	K	M
O	6	0	0	0	0	0	0
B	2	84	1	1	0	0	0
A	0	0	90	0	0	0	0
F	0	0	15	149	1	1	0
G	0	0	16	5	250	0	1
K	0	0	0	0	1	259	1
M	0	0	0	0	0	0	27

Note. [a] In this case, discrepancies affecting five subtypes are considered correct classifications.

percentage that fulfills the expected interval value criteria for any individual index, which also allowed us to assign an uncertainty factor.

Uncertainty is an important factor to consider in the approach to problem solving. Even for experts it is not always possible to

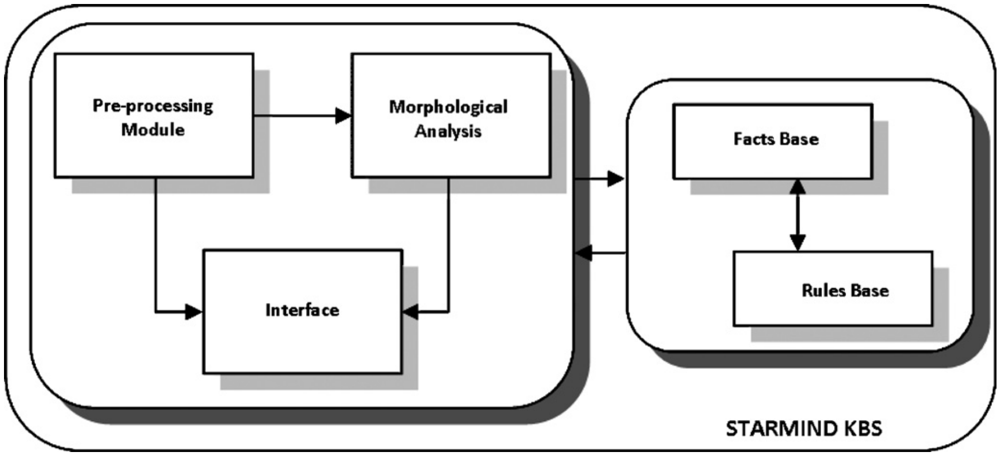

Figure 4. Structure of STARMIND expert system.

reach a decision with absolute certainty. This actually highlights another ES ability, which is to obtain more accurate diagnoses than those obtained by beginners in real-world environments characterized by uncertain information. The uncertainty may arise from several sources: loss of information, instrumental error or noise in scientific measurements, observational subjectivity, uncertainty in judgment, incompleteness of the domain theory, random events, and so on. Experts make assumptions about information that is not entirely available and take decisions that are often biased by uncertainty factors and limited situations. Hence the fuzzy logic approach, which is based on the consideration of certainty factors (CFs), is associated with each of the spectral indexes and allows us to simulate expert diagnoses.

From an operational point of view, the developed system can be divided into two main logical modules: the analysis module and the classification module. This structure is shown in Figure 4.

The analysis module is handled by the user and allows him to visualize and identify features and analyze the complete spectrum of each star in a clear and understandable way. It carries out a morphological analysis of the stellar spectra, which includes the study and measurement of all the spectral indexes needed for the classification. It can also extract and highlight diverse regions and even compare the problem spectra to those of the reference catalog by superposing them. The input of this module consists of the spectra that require classification; the output consists of a collection of values of the different spectral indexes, which will become the input data flux of the classification module.

The classification module is actually an ES of which the user only sees the result: a leveled classification of the stars. The input of this module consists of the values of the spectral indexes that were obtained in the analysis module. The output is a classification of the input spectra that includes a credibility factor. The following section will show how this classification covers two levels: global classification (early, intermediate, and late), and a classification at the spectral-type level. The results of the classification module are listed in the analysis module interface.

3. STARMIND: SYSTEM DESCRIPTION

Since an ES solves problems that typically require human expertise, its inferences need to be based on some knowledge provided by an expert. From this point of view, it is a device that can also be referred to as a KBS. According to this definition, an ES has two main components: the inference engine, i.e., the methodology to reason, which makes the inferences, and the knowledge base, which contains the knowledge of a given domain.

The design of the knowledge base must follow syntax and semantics that are appropriated to the inference engine that is to be used. In other words, knowledge needs to be expressed in some formal way so as to be used by an ES. Possible paradigms to represent knowledge in the frame of AI area are weather frames, semantic nets, and production rules. For further explanation, see Nillson (1982) and Winston (1992).

The selected parameters for spectral classification and the limiting values of each type were included in the ES in the shape of fuzzy rules. The base of rules is the part of the system where the human classification criteria are reproduced. The STARMIND base of rules decision tree is shown in Figure 5; the hierarchical decision rules and compliance percentages for spectral discrimination are presented in Table 3. We adopted production rules of the IF-THEN type to implement this module because they easily reproduce the reasoning followed by the experts in the field. The conclusions allude to the two levels of spectral classification (global and types).

The classification module actively communicates with the base of facts, where the descriptive information about the specific spectrum that is being analyzed at present is stored. We applied the Buchanan & Shortliffe (1984) methodology to carry out an evolution that includes fuzzy sets and membership functions, contextualized for each spectral type and allowing superposition between them. In addition, we obtain the spectral classification of stars with a probability value that indicates the confidence grade (CF). Sometimes this module can conclude an alternative classification of the spectra, e.g., when obtaining a first classification with a significantly small truth value. Some examples of this reasoning strategy are shown in Figures 6 and 7.

The developed expert system stores the information that is necessary to initiate the reasoning process in the base of facts. This descriptive knowledge of the spectra that are to be classified is represented by means of frames, i.e., objects and properties structured by levels. We opted for this model because it is the simplest and most adequate to transfer the analysis data to the classification module, and because it allows the equivalence between analysis data and knowledge. The knowledge of the base of facts includes general information, such as the names of

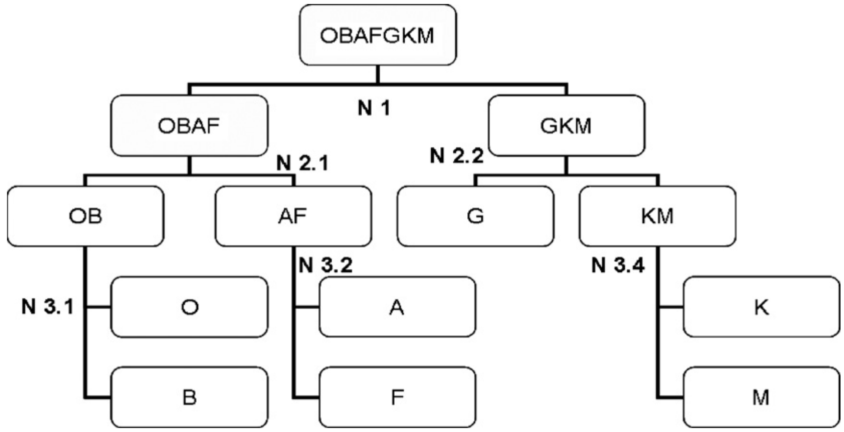

Figure 5. STARMIND base of rules.

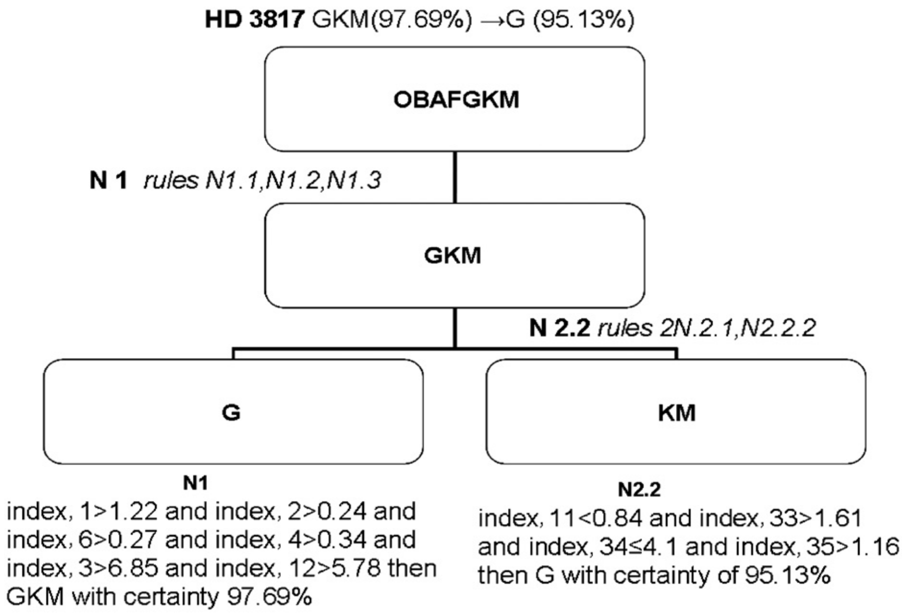

Figure 6. STARMIND example of classification for star HD 3817. Indexes are numbered as in Table 1.

the stars, and the results of the morphological analysis, i.e., the value of the spectral indexes.

The knowledge that is initially stored in the working memory will be used to start the reasoning process. In general, the ES explores the working memory in search of specific data to execute the rules of the rules base. The facts base communicates actively with the rules base and, along with the inferences engine, directs the process of spectral classification. The rules base module communicates with the facts base, because the facts stored in the working memory match with the left side of the rules.

Figures 6 and 7 illustrate the KBS reasoning, including the confidence percentage calculation. The conflict resolution strategy used by the monitoring system (i.e., the way it decides which rule to follow when the conditional parts of more than one rule are satisfied) is the means-ends analysis (MEA) approach that OPS-R2 inherits from its predecessors. In addition, the MEA strategy drives the identification and satisfaction of a succession of goals on the path to fulfill a global objective (see Forgy 1981 and Hayes-Roth et al. 1983 for details).

The strategy used for the reasoning process combines categorical methods (guided reasoning) with a method based on CFs. CFs reflect the certainty of each rule, not the success rate. While descending the decision rules tree, these CFs decrease in value due to the successive multiplication of the CFs of the different rules applied. In this way, the information is propagated along the reasoning process in order to define a final CF. In the example shown in Figure 6, HD 3817 is classified as a G-type star with a high CF, since each measurement in the facts base matches with the rules for G stars stored in the rules base.

The example in Figure 7 shows the classification of HD 10307 (a G1 star), in this case with a low CF. Molecular bands in this star are weak, so at level N1 the rules base cannot discern between OBAF and GKM and both branches are followed to the second level. At level N2.2 (G-KM), the system deduces that the star is a G-type, since all the rules for this type are fulfilled, and the relative confidence factor is 47.87%. At level N2.1, only the rules for sub-branch AF are fulfilled, so the system has to discern among A and F types by exploring the rules at level N3.2. Some of the rules for an F-type star are satisfied and the system reaches an F-type classification with a low CF (22.50%). Since the classification of the star as a G-type has a significantly higher CF (47.87%), the system concludes that HD 10307 is a G-type star. As these examples show, the CFs at

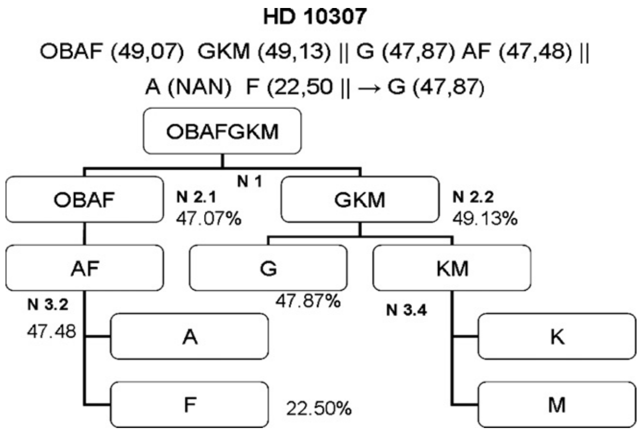

Figure 7. STARMIND example of classification for star HD 10307 showing the relative certainty factors.

different levels of classification are always relative, as well as it is the final value of relative confidence. The system generates a deterministic classification, but since it could be interesting for the user to follow the reasoning process of the classification system, we have included an explanation module in the base of rules. This module is based on transmitting the sequence of executed rules to the analysis module, where it is shown to the user in a simple and accurate way. As a result, the explanation module acquires added value and becomes a didactical tool in the training and formation of stellar spectroscopists. The output of the classification module is the two-level classification of the input spectra (global: early-OBAF, late: GKM; and spectral types), and the explanation of the system's reasoning. These results are transmitted to the analysis module and shown to the users through the interface. This module was implemented in OPS-R2 (Forgy 1981). The analysis module interface was developed in Borland C++ Builder 6.0, integrating also certain visual components that were developed in Visual Basic (VBX) and originally designed for the visualization of signals gathered by an analog data acquisition card.

4. RESULTS

4.1. A Spectral Database for System Evaluation

The performance of STARMIND ES was evaluated against a public database of stellar spectra: the INDO-US Library of Coudé Feed Stellar Spectra by Valdes et al. (2004). This library consists of spectra for 1273 stars, selected to provide broad coverage of the atmospheric parameters such as effective temperature, surface gravity, and [Fe/H], as well as spectral types. We have used the standard merged type of spectra (see Valdes et al. 2004 for details) for which the wavelength sampling goes from 3465 to 9469 Å in steps of 0.4 Å. From the original set of stars we selected a sample of 910 stars, avoiding cases with spectral gaps and stars already in the MK standard's database. The fluxes are continuum calibrated to a normalized flux density system. Stars in the library were assigned a spectral type from SIMBAD, and information about the atmospheric parameters is also provided with a reference code. The distribution of metallicities in the selected subsample is shown in Figure 8. The limitations and singularities of parameter determination and coverage are discussed in the above-mentioned paper.

4.2. Confusion Matrix

A total of 723 spectra out of 910 were assigned by STARMIND as an MK type consistent with the type provided in the INDO-US Library. This amounts to 79.5% as agreement percentage, with a mean error in stellar types of 0.23. The confusion matrix (Kohavi & Provost 1998) is a display tool used in the field of AI to inspect the performance of a supervised classification system. It contains information about actual and predicted classifications: the columns contain the number of predictions of each class and the rows represent instances in the real classes. One of its benefits is that it allows us to easily observe whether the system is confusing a particular pair of classes.

The confusion matrix that corresponds to STARMIND performance on the INDO-US Library is shown in Table 4. The numbers reflect the agreement rate for each spectral type. We can observe that the errors are mainly located in contiguous types, both the dispersion of A-type stars and the confusion of G-type with K-type stars being remarkable.

We suspect that most classification errors in our system could be related to "border problems," due to the diverging MK spectral resolution between the INDO-US Library (1 subtype), and our system (1 type). In fact, we observe that many of the disagreements correspond to the stars that are classified in the library with subtypes 0 or 9 (e.g., a B9 star classified by STARMIND as A). In order to evaluate this border effect, we elaborate a new confusion matrix, where in the case of a disagreement affecting only 1 subtype the STARMIND classification is considered to be correct. As mentioned in Section 1,

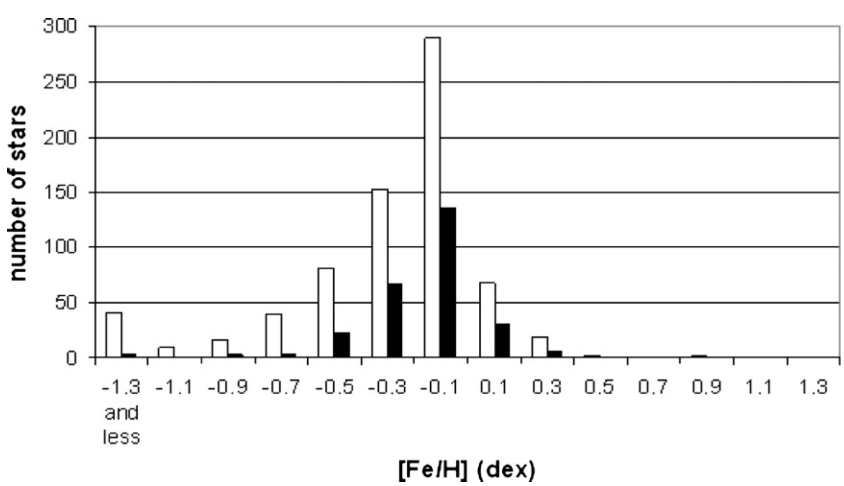

Figure 8. Distribution of metallicities in the MK reference database (black) and in a stars sample from the INDO-US Library (white).

a subsequent paper shall present a second system based on a hybrid strategy, and devoted to improving this classification scheme to the level of spectral subtypes. This system will be connected to our ES, constituting a hybrid system responsible for improving the classification results. Including 1 subtype discrepancies as good, STARMIND correctly classifies 807 out of 910 stars, the mean error in types being 0.13. The corresponding confusion matrix can be found in Table 5.

We see that the confusion of B stars as A-type almost disappears, that the confusion of G as K-type improves in 40% of the cases, and that there remains confusion among F-G and A types. The level of agreement is in this case 89%, the number of misclassified stars are 103, including 21 cases of F-type and 16 G-type stars wrongly labeled as A, and 34 G-type stars labeled as K stars.

We then decided to calculate a new confusion matrix where differences of five subtypes (a spectral type is divided into 10 subtypes) are included in STARMIND internal errors. The mean error is now 0.07 types. The new confusion matrix is shown in Table 6. STARMIND misclassification of G as K-stars disappears. The level of agreement is now excellent: 95%. We can conclude that, as suspected, the main discrepancies were caused by frontier classification disagreements due to the STARMIND resolution of 1 MK type.

As can be observed in the confusion matrix of Table 6, the errors that persist with some significance are the misclassifications of F and G as A-type stars. In order to find a possible explanation, we studied the distribution of metallicities of the 31 stars involved (when available). We find that all but one of the samples are low-metallicity stars, the mean value for F stars being [Fe/H] $= -1.15$ and [Fe/H] $= -2.0$ for G stars. The distribution of metal content for the complete sample of F and G stars shows a rather normal distribution around the solar value, with a sparsely populated tail of low-metallicity stars.

The degeneration between temperature and metal content is a well-known problem: stars with low metal content present spectra that resemble those of earlier type stars with higher temperatures.

4.3. The Degeneracy Among Metallicity and Spectral Type for A-F-G-Type Stars

For decades, the degeneracy between T_{eff} (spectral type) and metallicity complicated the study of the chemical history of the Galaxy. Nowadays, it has its sequel in extragalactic astrophysics, where degeneracy between age and metallicity continues to be a controversial problem in studies of spectral synthesis populations in galaxies (see the recent review by Vazdekis 2008).

In order to deal with the misclassification of low-metallicity F and G stars, we decided to equip STARMIND with some control rules that reinforce the classification of stars as A-type. H lines are strong in A-type stars, and so are Ca II lines, whereas the *G* band appears around F2 stars.

Once the system classifies a star as an A type, the values of index 20 (Hδ flux) and index 51 (*G*-band flux) are measured, and a simple pair of rules tests the classification:

1. If index 20 $\leqslant$ 0.4, then the star is a low-metallicity F or G star. In contrast, if index 20 $\geqslant$ 0.5, then the star is an A type.
2. If index 20 belongs to the (0.4, 0.5) interval, then the *G*-band rule is executed.
3. If index 51 $\geqslant$ 1.2, then the stellar type is F or G; if not, the star is an A-type star.

We applied these rules to the 31 F and G misclassified stars, obtaining a correct classification for all but one star. The next step consists of separating low-metallicity F from low-metallicity G-type stars. We used indexes 39 (3933 Ca II line flux) and 20 (again Hδ flux). The implemented rules sequence was as follows:

1. If index 39 $\leqslant$ 0.52, then the star type is G, while if index 39 $\geqslant$ 0.55 the star is an F-type star.
2. Intermediate values for index 39, belonging to the (0.52, 0.55) interval, imply that the system needs to execute the rule based on index number 20.
3. If index 20 $\leqslant$ 0.28, then the stellar type is G, while if index 20 is greater the star is an F type.

These rules completely separate F and G low-metallicity stellar types in our sample. Taking into account this new implementation, the STARMIND performance is now 82.7% (753 stars out of 910 correctly classified), 92% if we consider correct the cases with errors 1 subtype of discrepancy (837 correct classifications), and 98.3% considering five subtypes inside the system internal errors (895 correct classifications).

5. CONCLUSIONS

1. We have proved the suitability of STARMIND ES to perform automated classification of stellar spectra in the MK system. We have placed emphasis on the description of the system, because we think that this AI technique is still not well known among the astrophysical community. ESs are computer programs that try to imitate human reasoning through the use of AI techniques and reference to a database of knowledge that compiles the experts' understanding and expertise. For the first time such a system is applied to MK classification. We believe that an extensive explanation of a utility as the one presented, together with its didactical value, deserves the astrophysical community's interest.
2. In order to elaborate the set of rules that reflect the specific knowledge, a database of MK template spectra was built using both public libraries of MK standards and ad hoc telescopic observations. The experts knowledge was translated to a set of 64 morphological spectral features or spectral indexes, whose measurement was automated. The MK database was used to evaluate each index suitability to discern among spectral types. Statistical methods (PCA) allowed us to reduce the number of indexes to 30 items. Uncertainty factors were assigned to the indexes by considering the percentage of MK standards that fulfill limiting values for the indexes.
3. The STARMIND structure, in particular the base of rules and confidence factors at the different levels of classification, is explained, and its performance analyzed by means of classification examples. A user interface allows us to follow the reasoning of the system until it reaches a specific classification. This fact highlights one relevant application of our system: its ability to be used as a tool dedicated to the formation of beginning stellar spectroscopists in MK classification. The other technique that is most frequently used for automated spectral classification, ANNs, reaches a specific conclusion that cannot be followed back for didactical purposes.
4. The performance of the system was evaluated against a sample of 910 spectra from the INDO-US Library of stellar

spectra. The study of the confusion matrix among spectral types allowed us to identify the main sources of errors. Confusion between subsequent types is shown to be mostly limited to the range of 1–5 stellar subtypes and hence resolvable by improving the classification resolution to stellar subtypes. This problem will be tackled by using a hybrid system based on both ES and ANNs and presented in a forthcoming paper. Another source of errors is found to be the presence of some low-metallicity intermediate-type stars. This problem was solved by implementing new rules that reinforce the classification of A-type stars.

5. Finally, the results on the INDO-US test library provide evidence that it is possible to obtain an accurate diagnosis of a particular spectrum. STARMIND success rate is 82.7%, but increases to 92% when errors in one spectral subtype are considered acceptable as internal errors, and even to 98.3% when errors up to five spectral subtypes are taken inside the system internal errors. This result is an excellent starting point to complete an automated AI-based tool for classification of spectra in the MK system.
6. The system will be available to the astronomical community through the SVO Web site.

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