PCA-based inversion of stellar fundamental parameters from high-resolution Echelle spectra

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Abstract

The general context of this study is the inversion of stellar fundamental parameters from high-resolution Echelle spectra. We aim at developing a fast and reliable tool for the post-processing of spectra produced, in particular, by the Espadons and Narval spectropolarimeters. Our inversion tool relies on principal component analysis. It allows reduction of dimensionality and the definition of a specific metric for the search of nearest neighbours between an observed spectrum and a set of synthetic spectra. Effective temperature, surface gravity, total metallicity and projected rotation velocity are derived. Our first tests, essentially done from the sole information coming from the spectral band that the RVS spectrometer will observe from the GAIA space observatory, and with spectra from mainly FGK-dwarfs are very promising. We also tested our method with a few targets beyond this domain of the H–R diagram.

1 Introduction

This study is concerned with the inversion of fundamental stellar parameters from the analysis of high resolution Echelle spectra. Hereafter, we shall focus indeed on data collected since 2006 with the Narval spectropolarimeter mounted at the 2-m aperture Télescope Bernard Lyot (TBL) telescope located at the summit of the Pic du Midi de Bigorre (France). We investigate, in particular, the capabilities of the principal component analysis (hereafter PCA) for setting-up a fast and reliable tool for the inversion of stellar fundamental parameters from these high-resolution spectra.

The inversion of stellar fundamental parameters for each target that was observed with both Narval and Espadons spectropolarimeters constitutes an essential step towards (i) the further post-processing of the data like e.g., the extraction of polarimetric signals (see e.g. Paletou 2012) but also (ii) the exploration or data mining of the full set of data accumulated over the last 8 years now. In Section 2, we briefly describe the actual content of such a database.

Our usage of PCA for such an inversion process is strongly influenced by the one routinely made in solar spectropolarimetry during the last decade after the pioneering work of Rees et al. (2000). Very briefly, the reduction of dimensionality allowed by PCA is further used for building a specific metric from which a nearest neighbour(s) search is done between an observed data set and a learning database. The latter most often rely on synthetic data generated from input parameters properly covering the a priori range of physical parameters expected to be deduced from the observations themselves. Fundamental elements of our method and its basic capabilities are exposed in Sections 3 and 4. One of its originality relies on the simultaneous inversion of the effective temperature $T_{\text{eff}}$, the surface gravity $\log g$, the full metallicity $[\text{M}/\text{H}]$ and the projected rotation velocity $v_{\sin i}$. 


In this study we restrict ourselves, on purpose, to the spectral domain that will be observed by the RVS spectrometer flying on-board the space mission GAIA (Katz et al. 2004). The RVS will operate in a spectral domain of the order of 847–874 nm, in the vicinity of the Ca\textsuperscript{ii} infrared triplet, a domain whose pertinence for the further characterization of the observed stars was discussed by Munari (1999). This allows us to anticipate reasonable stellar parameter inversions for stars from B8 to M8, a very large range of spectral types similar to the actual content of our database.

The conditioning of observed spectra prior to their ingestion into our inversion tool is detailed in Section 5, and first tests made with solar spectra observed by reflection over the surface of the Moon are discussed in Section 6. More intensive tests are presented and discussed in Section 7, mainly for FGK-dwarf stars for which fundamental parameters are already available from the so-called SPOCS catalogue (Valenti & Fisher 2005). We then briefly discuss in Section 8. preliminary tests using spectra from giant stars as well as hotter and cooler than FGK stars.

2 The source of data

We mainly used Narval data available from the public database TBLegacy\textsuperscript{1}. Narval is a state-of-the-art spectropolarimeter operating in the 0.38-1 µm spectral domain, with a spectral resolution of 65,000 in its polarimetric mode. It is an improved copy, adapted to the 2-m TBL telescope, of the Espadons spectropolarimeter, in operations since 2004 at the 3.6-m aperture CFHT telescope.

The TBLegacy database is operational since 2007. It is at the present time the largest on-line archive of high-resolution polarization spectra. It hosts data that were taken at the 2-m TBL telescope since December 2006. So far, more than 70,000 spectra have been made available, for more than 370 distinct targets all over the Hertzsprung-Russell diagram. More than 13,000 polarized spectra are also available, mostly for circular polarization. Linear polarization data are very seldom still and amount to a few hundreds spectra, but they are equally available.

At the present time, the TBLegacy database provides no more than Stokes $I$ or $V/I_c$ spectra calibrated in wavelength. Stokes $I$ data are either normalized to the local continuum or not. We have however plans to extend it (i) to Espadons data, from the CFHT telescope and (ii) to propose higher-level data, such as pseudo-profiles resulting from line addition and/or least-squares deconvolution (see e.g., Paletou 2012), activity indexes as well as stellar fundamentals parameters. The latter’s knowledge, besides being obviously interesting by themselves, is also indispensable to any further post-processing of these high-resolution spectra.

3 PCA inversion

Our PCA inversion tool is strongly inspired by magnetic and velocity field inversion tools which have been developed to complement solar spectropolarimetry (see e.g., Rees et al. 2000). Improvements of this method have been recently exposed by Casini et al. (2013). Hereafter we describe its main characteristics, in the context of our study.

3.1 The training database

Let us call $\{S_i(\lambda)\}$ our training database of synthetic stellar spectra. Each of these spectra is characterised by a limited number of physical parameters which serve as input parameters

\footnotesize{\textsuperscript{1}http://tblegacy.bagn.obs-mip.fr/}
for the numerical code producing them. Usually, for so-called *standard* stellar models, the minimal set of parameters is the effective temperature of the star, $T_{\text{eff}}$, its surface gravity, log $g$, its *total* metallicity [M/H] (even though the specific iron abundance [Fe/H] is also frequently used) and a so-called microturbulent velocity $\xi$ which is an artificial contributor to line widths, in addition to thermal (or Doppler) broadening.

Because a significant part of our database is constituted of moderately, say $v_{\text{sini}} > 10$ km s$^{-1}$ to fast rotators, we adopted the collection of spectra already computed and made available by Munari et al. (2005). They used Castelli & Kurucz’ Atlas code and they originally considered parameters spanning ranges from 3500 K to 47 500 K for $T_{\text{eff}}$, 0. to 5. for log $g$, -2.5 to 0.5 for [M/H], two distinct values, 0. and 0.4 for [$\alpha$/H], microturbulent velocities $\xi$ from 1 to 4 km s$^{-1}$ and projected rotation velocities $v_{\text{sini}}$ ranging from 0 to 500 km s$^{-1}$.

Our training database contains about 34 757 synthetic spectra after we limited ourselves to those spectra for which [$\alpha$/H]=0 and $\xi = 2$ km s$^{-1}$. Also, only the so-called “new ODF” (where ODF stands for opacity distribution function; see Castelli & Kurucz 2003) spectra were selected for $T_{\text{eff}} < 10 000$ K. And hereafter we shall focus on the inversion of the set of the four parameters \{$T_{\text{eff}}; \log g; [\text{M/H}]; v_{\text{sini}}$\} for each of our observed spectra.

It is also important to note that we used Munari et al. (2005) spectra computed for a resolving power of $R = 20000$ i.e., about a factor of 3.25 less than the one of the observed spectra we want to process. We shall come back to this point in Section 5.

### 3.2 Reduction of dimensionality

Each spectra from Espadons and Narval spectropolarimeters provide of the order of 250 000 flux measurements vs. wavelength across a spectral range spanning from 0.38 to 1 $\mu$m typically. Hereafter we consider spectra obtained in the polarimetric mode at a resolvance $R = 65 000$. Indeed, since they result from the combination of 4 successive exposures, mainly for the purpose of extracting properly polarization signals (see e.g., Semel et al. 1993), these spectra have higher signal to noise ratio than “simple” Stokes I ones. Moreover, stellar parameters derived from this observing mode spectra can be directly used for the further post-processing of the multi-line polarized spectra (see e.g., Paletou 2012).

For this preliminary study, we restricted the spectral domain from which we shall invert stellar parameters to the one of the RVS instrument of the GAIA space mission, that is for wavelengths ranging from about 847 to 874 nm (Katz et al. 2004). Arguments in favor of the use of this very spectral domain can also be found in Munari (1999). Considering this, the matrix $\vec{S}$ representing our training database turns to be $N_{\text{models}} = 34 757$ by $N_{\lambda} = 1 569$.

Next we compute the eigenvectors $\vec{e}_k(\lambda)$ of the variance-covariance matrix

$$\vec{C} = (\vec{S} - \bar{S})^T \cdot (\vec{S} - \bar{S}),$$

where $\bar{S}$ is the mean of $\vec{S}$ along $N_{\text{models}}$. Therefore $\vec{C}$ is a $N_{\lambda} \times N_{\lambda}$ matrix. In the framework of principal component analysis, reduction of dimensionality is achieved by representing the original data by a limited set of projection coefficients

$$p_{jk} = (S_j - \bar{S}) \cdot \vec{e}_k,$$

with $k_{\text{max}} \ll N_{\lambda}$; in the following, for the processing of all observed spectra, we shall adopt $k_{\text{max}} = 14$.

The most frequent argument supporting the choice of $k_{\text{max}}$ relies on the accuracy achieved for the reconstruction of the original set of $S_j$’s from a limited set of eigenvectors (see e.g., Rees et al. 2000 or Ramírez Vélez 2010). However the potential effect of noise on the observations should also be taken into account (see e.g., Socas-Navarro et al. 2001). We shall discuss this specific point in the next Section.
Table 1: Maximum differences between input and inverted parameters for noisy spectra vs. the number of eigenvectors considered. All spectra of the learning database were processed after they were perturbed by a white noise characterized by a 0.005 per pixel standard deviation.

| $k_{\text{max}}$ | $\Delta T_{\text{eff}}$ [K] | $\Delta \log g$ | $\Delta [\text{M/H}]$ | $\Delta v_{\sin i}$ [km s$^{-1}$] |
|------------------|-----------------------------|-----------------|----------------------|-----------------------------|
| 8                | 375                         | 1.2             | 0.32                 | 1.5                         |
| 10               | 250                         | 0.5             | 0.18                 | 1.                           |
| 12               | 0                           | 0.5             | 0.                   | 1.                           |
| 14               | 125                         | 0.32            | 0.                   | 2.5                         |
| 16               | 250                         | 1.15            | 0.26                 | 16.5                        |

Practically, we also found convenient to use $p_{jk}$’s both centered to their average $\bar{p}$ and normalized to their standard deviation $\sigma_p$. It is a common practice in the field of pattern recognition, since it guarantees that those coefficients from which we shall define the specific metric used for the nearest neighbour(s) search will have comparable effects (on the comparison between spectra).

### 3.3 Nearest neighbour(s) search

The above described reduction of dimensionality allows one to perform a fast and reliable inversion of observed spectra, once the latter have been (i) corrected of the wavelength shift vs. synthetic spectra because of the radial velocity of the target, (ii) renormalized as accurately as possible, (iii) degraded in spectral resolution to be comparable to the $R = 20000$ of the synthetic spectra and finally (iv) resampled in wavelength as the collection of synthetic spectra. We shall come back to these various stages in the next section, however once they have been achieved, the inversion process is the following.

Let $O(\lambda)$ the observed spectrum made comparable to synthetic ones. We now compute the reduced set of projection coefficients

$$\varrho_k = \frac{(O - \bar{S}) \cdot \vec{e}_k - \bar{p}}{\sigma_p},$$

for $k = 1, \ldots, k_{\text{max}}$. The nearest neighbour search is therefore done by seeking the minimum of the squared Euclidian distance

$$d_j^{(O)} = \sum_{k=1}^{k_{\text{max}}} (\varrho_k - p_{jk})^2,$$

where $j$ spans the number, or a limited number if any a priori is known about the target, of distinct synthetic spectra in the training database. In practice, we do not limit ourselves to the nearest neighbour search, although it already provides a relevant set of parameters. Because PCA-distances between several neighbours may be of the same order, we adopted a procedure consisting on considering all neighbours in the domain

$$\min(d_j^{(O)}) \leq d_j^{(O)} \leq 1.2 \times \min(d_j^{(O)}),$$

and derive stellar parameters as the (simple) mean of each set of parameters (\(T_{\text{eff}}; \log g; [\text{M/H}]; v_{\sin i}\)) characterising this set of nearest neighbours (A. López Ariste, private communication).
4 The effect of noise on the inversion process

Before processing any real observed spectra with our PCA-based inversion tool, we need to investigate on the potential effect of noise. To do so we have affected randomly chosen synthetic spectra \( S_{i}(\lambda) \) to various and controlled gaussian white noise-levels, and estimated how it affects the inversion process. Table 1. summarizes results of such an investigation for a noise level characterized by a standard deviation \( \sigma = 0.005 \). For various values of \( k_{\text{max}} \) i.e., the number of eigenvectors onto which we project the observed spectra, we reported the maximum difference observed for each of the 4 stellar parameters we want to estimate. These results provide us with an adequate choice for \( k_{\text{max}} \) which does not appear as the best for single parameters (e.g. \( T_{\text{eff}} \)) but which gives the best trade-off considering the full set of physical parameters we want to invert.

After several experiments of this kind, we noticed also that the maximum errors reported for each parameter do no always vary regularly with \( k_{\text{max}} \), depending on the noise level considered. This suggests that considering projections on a complete, uninterrupted, sequence of eigenvectors may not be the optimal choice and that a combination of selected “orders” may be a better choice for the reduction of dimensionality and, therefore, the definition of the metric we shall use for the inversion process.

5 Conditioning of the observed spectra

The first and obvious task to perform on observed spectra is to correct for their wavelength shift vs. synthetic spectra computed at radial velocity \( V_{\text{rad}} = 0 \). The radial velocity of the target at the time of the observation is deduced from the centroid, in a velocity space, of the pseudo-profile resulting from the “addition” (see e.g., Paletou 2012) of the three spectral lines of the Ca\,\text{ii} infrared triplet whose rest wavelengths are, respectively, 849.802, 854.209 and 866.214 nm. Once \( V_{\text{rad}} \) is known the observed profile is set on a new wavelength grid, at rest.

A second step consists in degrading the resolution of the initial spectra to the one of the synthetic spectra computed for \( R = 20\,000 \). This is done by convolving the initial observed profile by a Gaussian profile of adequate width. Then we resample the wavelength grid down to the one common to all synthetic spectra, and we interpolate the original spectra onto the new wavelength grid.

Finally, we have to correct for unproper normalization of the Stokes \( I \) flux to the local continuum. This issue has been very well discussed in Gazzano et al. (2010) as well as in Kordopatis et al. (2011), and we adopted their procedure.

6 First tests with solar spectra

First tests of our inversion method were performed using solar spectra observed by the 2-m aperture TBL telescope by reflection over the surface of the Moon in March and June 2012.

The synthetic spectrum having the minimal PCA-distance with the observed spectrum have model parameters \( T_{\text{eff}} = 6000 \text{ K}, \log g = 4.5, \left[ \text{M/H} \right] = 0 \) and \( \text{vsini} = 5 \text{ km s}^{-1} \), which slightly overestimate canonical values of \( T_{\text{eff}} = 5780 \text{ K}, \log g = 4.4 \) and \( \text{vsini} \) about 2 km s\(^{-1}\) (see e.g., Pavlenko et al. 2012). Considering the “bulk” of nearest neighbours in the range defined by inequalities (5), we derive more accurate parameters such as \( T_{\text{eff}} = 5772 \text{ K}, \log g = 4.3, \left[ \text{M/H} \right] = 0 \) and \( \text{vsini} = 2.2 \text{ km s}^{-1} \). Typically of the order of 20 neighbour-models are identified with our procedure and for our solar spectra.

The relevance of the PCA-distance on which rely our inversion process can be verified by the examination of the characteristics of the set of nearest neighbours we can identify. In the solar spectrum case, we find: 9 models bearing \( T_{\text{eff}} = 5750 \text{ K}, \) 6 models with \( T_{\text{eff}} = 5500 \text{ K} \) and
Figure 1: The top figure displays normalized flux from the observation of the Sun in reflection over the Moon made at the TBL with the Narval spectropolarimeter (blue) and the nearest PCA-distance synthetic spectrum (red). The latter correspond to parameters $T_{\text{eff}}=6000$ K, $\log g=4.5$, $[\text{M/H}]=0$ and $v\sin i=5$ km s$^{-1}$. The bottom figure displays the relative error vs. wavelength between the two spectra.

Figure 2: Stellar fundamental parameters for a set of objects common to Valenti & Fisher (2005) SPOCS catalogue and our database. Thin lines indicates respectively $\pm 300$ K range in $T_{\text{eff}}$, $\pm 0.5$ dex in $\log g$ and $\pm 0.3$ dex in $[\text{M/H}]$, values adopted after Kordopatis et al. (2011, 2013). For projected rotation velocities, they indicate a $\pm 10\%$ range.
Table 2: Characterization of the differences between our inverted parameters and these provided by the SPOCS catalogue.

| Parameter (θ) | <Δθ> | σ_Δθ |
|---------------|-------|-------|
| T_{eff}       | -70   | 202   |
| log g         | -0.08 | 0.30  |
| [M/H]         | 0.008 | 0.11  |

as many at 6000 K and one at 6250 K. For the surface gravity we find: 9 with log g = 4.0, 6 with 3.5 and as many at 4.5 and just one at 5.0. Finally, concerning the projected rotational velocity, we find 8 models at 0, 7 at 2 km s$^{-1}$ and as many at 5 km s$^{-1}$. Note finally that all neighbours have [M/H] = 0.

7 Comparisons with the SPOCS catalogue

For another indispensable test of our method, we focused on targets in common between our database and the so-called “Stellar properties of observed cool stars” (aka. SPOCS) catalogue (Valenti & Fischer 2005). Targets are therefore limited to FGK-dwarf stars and we found 93 observed spectra with acceptable quality.

7.1 Main result

The same numerical procedure was adopted for all spectra, whatever their associated level of signal-to-noise. A more refined analysis may require to adapt the choice of $k_{\text{max}}$ to the latter.

Results are displayed in Fig. (2) where we plotted our results against SPOCS values, for each parameters we invert from the observed spectra. The color code, as well as the size of each dot are proportional to the signal-to-noise level of the observed spectra. The bluer and smaller dots are for these spectra having the lowest signal-to-noise ratio in our sample.

The difference between ours and SPOCS parameters can be characterized by the values provided in Table 2.

7.2 About the outliers

Hereafter we examine with more details the various determinations of each physical parameter, besides from SPOCS values, for the major outliers we identified.

7.2.1 Effective temperature

It is interesting to note that all the estimate outside a ±300 K limits come from spectra with relatively low signal-to-noise ratio. As compared to values taken from the SPOCS catalogue for our sample, we notice a bias of the order of 70 K and a dispersion of 202 K. For the spectral domain from which we proceed for the inversion of $T_{\text{eff}}$ i.e., the RVS of GAIA, our values and their comparison with existing catalogues can be compared, to a certain extent, with the ones recently derived by Kordopatis et al. (2011, 2013).

The most conspicuous outlier is the young stellar analog, EK Dra, for which we derive an effective temperature about -565 K away from the one given by the SPOCS catalogue. König et al. (2005), for instance, report an effective temperature about -150 K lower than the one from SPOCS, but still significantly higher than ours. However, the spectrum we used for EK Dra exhibits features such as central emission at the core of the infrared triplet spectral
lines, which is characteristic of stellar activity but out of reach from standard atmospheric modelling. This shows one of the limit of our inversion tool, but in fact of any of such tools based on standard atmospheric models which are, de facto, unable to adequately describe such a manifestation of stellar activity through spectral line “unconventional” shapes.

7.2.2 Surface gravity

The surface gravity is certainly the most difficult stellar parameter to invert from spectroscopy. One of the most important outlier in our sample is the red giant branch star HD 25069 for which our estimate of log $g$ is 2.8 against 3.5 from the SPOCS catalogue. However, values of the order of 3.2, and the more reasonable 0.4 dex difference with our own estimate, were reported by Jones et al. (2011) and Massarotti et al. (2008; and our estimate of $T_{\text{eff}}$ matches very well with these authors’ 4775 K too).

HD 208801 is a high-proper motion star of spectral type K2V. Our estimate of log $g$ is 3.1 which is significantly lower than the 3.9 extracted from the SPOCS catalogue. However Massarotti et al. (2008) again report of a surface gravity of 3.6 for this object, a value within 0.5 dex of our estimate.

HD 185395 is another high-proper motion star, of F4V spectral type. We notice a considerable 0.9 dex disagreement between our estimate and the log $g$ value of 4.0 given by the SPOCS catalogue. However, considering several other sources of data, such discrepancy would go down to 0.5 dex (see Cunha et al. 2000; Thévenin et al. 1986; Boesgaard & Lavery 1986).

HD 173667 is a variable star of spectral type F6V. We estimate its log $g$ at 4.8 instead of 4.0 from the SPOCS catalogue. However some authors provide values of 4.26 (Takeda 2007) and even as much as 4.5 (Boesgaard & Friel 1990).

7.2.3 Metallicity

The major outlier, at least outside the bounds of $\pm 0.3$ dex we adopted after Kordopatis et al. (2011, 2013) is HD 86728 with a +0.4 dex difference between our estimate (0.5) and the one of the SPOCS catalogue. According to Simbad, this target is yet another high-proper motion star of spectral type G3V. Takeda (2007) reported a metallicity [Fe/H] of 0.27, as well as an effective temperature of 5838 K closer to our 6108 K, and larger than the 5700 K we get from the SPOCS catalogue. Lee et al. (2011) provide [Fe/H] values of 0.15 and 0.21 also overestimating the one from the SPOCS catalogue.

7.2.4 Projected rotation velocity

One of the originality of our inversion tool is that we estimate the projected rotation velocity of stars $v_{\sin i}$. We are particularly interested in the analysis of the spectra of the fastest rotators in the actual sample. On the contrary we do not pay much attention to the bulk of determinations we made for, typically, $v_{\sin i}$’s lower than 5 km s$^{-1}$. More generally, we remind the readers here that most inversion tools just ignore the effects of rotation implicitly by using synthetic spectra calculated at $v_{\sin i} = 0$.

At $v_{\sin i}$ larger than 15 km s$^{-1}$ the two most apparent outliers are indeed EK Dra and τ Boo. About EK Dra, the SPOCS catalogue provides a $v_{\sin i}$ of 16.8 km s$^{-1}$ while our estimate is significantly larger, about 26 km s$^{-1}$. It is interesting to note that values of the order of 23 km s$^{-1}$, in much better agreement with our determination, have been reported by White et al. (2007). The second important outlier is τ Boo (A) for which the SPOCS catalogue provides a $v_{\sin i}$ of 15 km s$^{-1}$ while our estimate is about 19 km s$^{-1}$. Again a $v_{\sin i}$ of about 18 km s$^{-1}$ has been recently reported by Martínez-Arnaiz et al. (2010).
Table 3: Derived stellar parameters for FGK giants, A and M stars.

| Object   | $T_{\text{eff}}$ | log\text{g} | [M/H] | $v \sin i$ |
|----------|------------------|-------------|-------|------------|
| GL 205   | 3750             | 4.8         | 0.0   | 3.         |
| Arcturus | 4250             | 2.0         | -0.5  | 5.         |
| Sirius   | 10500            | 4.5         | 0.5   | 10.        |

Figure 3: Same as figure 1 for Sirius A.

8 Beyond the FGK-dwarfs domain

Our database of spectropolarimetric data already covers pretty well the H-R diagram. We are therefore interested in spanning most of it with basically the same tool. Selected targets for these preliminary tests are indicated, together with the parameters we derived from their spectra, in Table 3.

A first excursion away from the FGK-dwarfs domain is to explore the luminosity class towards the giants domain. For that purpose, we used data from the K1.5III subgiant star Arcturus. Our 4250 K determination of its effective temperature is very close, within 30 K, to that of Prugniel et al. (2011). We derive a surface gravity about 2.0 in agreement with alternative estimates (e.g., Massarotti et al. 2008). Our [M/H] and $v \sin i$ values are also in pretty well identified ranges. Note that further tests with Pollux (K0III) data also gave excellent results.

For cooler stars, we picked spectra of GL 205, a M1.5V dwarf. Our values of $T_{\text{eff}}$, log\text{g} and [M/H] agree very well with those of Prugniel et al. (2011), and our $v \sin i$ determination agrees well with the one of Houdebine (2010). There is also a reasonable agreement with values recently derived by Neves et al. (2013).

Finally, we also tested our method with spectra of the A1V star Sirius (A). Our inversion of the effective temperature gives a value a bit larger than the 9870 K more recently reported (Hill & Landstreet 1993). [M/H] is also overestimated, but log\text{g} and $v \sin i$ are quite well determined. The agreement between the observed spectrum and the nearest neighbour
synthetic spectrum is however very good, as shown in Fig. (3).

9 Conclusion

We have experimented a fast and reliable PCA-based numerical method for the inversion of stellar fundamental parameters $T_{\text{eff}}$, $\log g$ and [M/H], as well as the projected rotation velocity $v_{\text{sin}i}$, from high-spectral resolution Echelle spectra taken from the Narval spectropolarimeter in operations at the 2-m TBL telescope. Our method is fast and easy to implement, and our first tests, mainly made for FGK-dwarf stars show fairly good agreement with reference values published by Valenti & Fischer (2005). Preliminary tests also suggest that the same tool will be applicable to FGK giants, cooler M stars and hotter stars of spectral type A.

We used it, so far, in the spectral domain which will be observed by the RVS instrument flying onboard GAIA i.e., in the vicinity of the infrared triplet of Ca II and without any help from additional (e.g., photometric) information, which is particularly challenging. However we can easily, either extend the spectral domain used by our inversion method, or combine analyses from several distinct spectral domains, in order to constrain further and refine the stellar parameter determination.

Another source of potential improvement relies on the content of the learning database. ATLAS standard models may not be the best choice for cool stars or for metal-poor stars for instance. It is also well-known that non-LTE effects may take place in the formation of the infrared triplet of Ca II, which affects the spectral lines central depressions. This issue was for instance mentioned in Kordopatis et al. (2011). Finally, we shall need synthetic spectra computed for a resolution comparable to the one of our observations and, ideally, including the effects of rotational broadening.

It is finally important to realize from the present study that PCA allows for a reduction of dimensionality of the order of 100 which is of great potential interest for the post-processing of high-resolution spectra covering a very large bandwidth like the ones of Espadons and Narval.

10 References

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