Stellar Atmospheric Parameter Measurement Postprint

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Abstract

Beginning with the significance of stellar research, this paper introduces the fundamental concepts and research importance of stellar atmospheric parameters; it elaborates on the classification of stellar parameter measurement methods into direct and indirect approaches. The review emphasizes indirect measurement techniques, encompassing photometric methods, infrared flux methods, Balmer line profile fitting, line ratio methods, line index methods, metallic line diagnostics, spectral template fitting, and machine learning methods. It highlights the advantages and extensive applications of spectral template fitting and machine learning methods in large-scale survey data. For high-resolution spectra, metallic line diagnostics remain highly favored by astronomers, while measurement results from infrared flux methods are frequently employed for calibration.

Full Text

Preamble

Survey of Stellar Atmosphere Parameter Estimation

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Abstract

Starting with the significance of stellar research, this paper introduces the fundamental concepts and importance of stellar atmosphere parameters. We discuss the classification of stellar parameter measurement methods into two major categories: direct measurement and indirect measurement, with particular emphasis on reviewing indirect techniques. These include photometric methods, the infrared flux method, Balmer line profile fitting, spectral line ratio methods, line

index methods, metal line diagnostics, spectral template fitting, and machine learning approaches. We highlight the advantages and widespread application of spectral template fitting and machine learning methods in large-scale survey data. For high-resolution spectroscopy, metal line diagnostics remains highly favored by astronomers, while measurements from the infrared flux method are frequently used for calibration.

Keywords: parameter estimation; stellar; spectroscope; machine learning

Astronomy is an ancient discipline that studies the formation and evolution of celestial objects in the universe. Stars are the most extensively and thoroughly studied objects in the cosmos. Born from interstellar material, stars evolve over billions of years into white dwarfs, neutron stars, or black holes while simultaneously feeding back into the interstellar medium. As the fundamental building blocks of galaxies—which constitute the dominant visible component of the universe—stars serve as the basis for kinematic and dynamical studies of star clusters, galaxies, galaxy mergers, and galaxy clusters, enabling investigation of the past, present, and future evolution of the entire cosmos. Thus, stellar research can be considered the foundation for understanding the universe.

Stars are luminous spheres of gas held together by gravity, composed primarily of hydrogen. In most cases, intense nuclear reactions continuously occur in stellar interiors, releasing enormous energy that maintains high-temperature, high-pressure conditions and generates sufficient pressure to counteract the weight of the outer atmospheric layers. With lifespans ranging from millions to hundreds of billions of years, stars appear as long-lasting luminous objects. Except for the Sun, stars are typically too distant for close-up investigation—even the Sun cannot be truly studied at close range. Consequently, astronomers must rely on observations and analysis of starlight, examining position, magnitude, and spectrum to study both external characteristics (direction, distance, velocity) and intrinsic properties (mass, radius, atmospheric composition, internal atmospheric structure, turbulence, pulsation, rotation, magnetic fields). Among these, measuring stellar atmosphere parameters forms the basis for all related stellar research.

1. Stellar Atmosphere Parameters

The stellar atmosphere refers to the directly observable portion of a star, representing the transition region between the stellar interior and the interstellar medium. Covering the core, radiative zone, and convective zone, the atmosphere can be further divided into several layers: the photosphere, chromosphere, chromosphere-corona transition region, and corona. The photosphere, the lowest layer of the stellar atmosphere and the star' s primary visible component, is where most stellar radiation originates before passing through the outer layers to reach the observer; stellar spots also occur in this layer. Consequently, stellar atmosphere parameters are primarily determined by the photosphere, with its thickness defined by a unit of optical depth. Typically, these parameters include effective temperature (T_{eff}), surface gravity ($\log g$), metallicity ([Fe/H]), and microturbulence velocity, constituting the main content of stellar atmosphere parameter measurements.

2. Direct Measurement

Direct measurement of stellar atmosphere parameters imposes extremely stringent requirements. For effective temperature (T_{eff}), defined as the temperature of a blackbody with equivalent luminosity per unit area and converted via the Stefan-Boltzmann law, observers must measure the star' s total flux across all wavelength bands from the ground (accounting for extinction effects) and determine the star' s angular diameter—the ratio of stellar diameter to distance. Precise direct measurement of angular diameters is generally possible only for stars very close to Earth, making such measurements extremely limited in number. Alternative methods such as interferometry and lunar occultation struggle to achieve high precision. Direct surface gravity measurement requires accurate determination of both mass and stellar radius, with eclipsing binary systems providing the best precision while single-star measurements remain exceptionally difficult. Currently, direct atmospheric parameters have been obtained for approximately 150 stars, with the Sun and Vega being the primary representatives.

3. Indirect Measurement

Indirect measurement represents the primary approach for determining stellar atmosphere parameters. The fundamental concept involves establishing a mapping or relationship between observational data and parameters using stars with known parameters, then applying this relationship to infer parameters for target stars. Specific indirect methods vary considerably, differing mainly in three aspects: data type, processing methodology, and optimization techniques. Data types are divided into photometric and spectroscopic data. Processing methods range from initial grid calibration and construction of empirical analytical functions (linear and nonlinear fitting) to template fitting (e.g., chi-squared minimization) and machine learning approaches. Optimization techniques involve improving the success rate, accuracy, and speed of algorithmic components.

3.1 Photometric Methods

Photometric observations offer significant advantages over spectroscopic observations: they enable rapid coverage of large sky areas or even the entire sky; achieve completeness to specific magnitude limits; obtain simultaneous multi-band data; and facilitate long-term monitoring of time-variable sources through extended observations. These advantages are difficult for spectroscopic surveys to match. Although large-area spectroscopic surveys now produce millions of spectra, this number remains far smaller than the actual stellar population. Consequently, while photometric data yield less accurate parameters than spectroscopic data, they can provide atmospheric parameters for vastly more stars, representing substantial applied value.

The photometric grid calibration method combines theoretically calculated relations for specific broadband photometric systems to establish mapping grids from photometry to effective temperature and surface gravity, calibrated using Vega or other standard stars. Reference [1] provides a mapping chart from photometric data to parameters that saw widespread use in early multi-band photometric surveys, achieving temperature precision of 200 K and surface gravity precision of 0.2 dex, though with low metallicity sensitivity and surface gravity estimates suitable only for Am-type stars. Reference [2] utilized models to calculate theoretical color indices.

Spectral Energy Distribution (SED) fitting represents another optimization approach using photometric data. Reference [3] describes the dominant photometric parameter measurement method at the time: constructing an SED from photometric data and fitting it with theoretical models to find the best match, thereby estimating effective temperature, surface gravity, metallicity, and microturbulence. This SED fitting method yields temperature errors of a few hundred Kelvin but less accurate other parameters, particularly metallicity. Reference [4] employs Bayesian theory with the Hertzsprung-Russell diagram as a prior distribution to estimate temperatures and extinction for Hipparcos FGK stars from 2MASS photometry and parallax data, achieving 200 K temperature precision and 0.2 magnitude extinction precision. Reference [5] introduces the VOSA software, which constructs SEDs from Galaxy Evolution Explorer (GALEX), Sloan Digital Sky Survey (SDSS), Two Micron All-Sky Survey (2MASS), Wide-field Infrared Survey Explorer (WISE), and Visible and Infrared Survey Telescope for Astronomy (VISTA) data to estimate parameters for M-type stars.

The color index-temperature relation method exploits the strong relationship between color indices (magnitude differences between two bands) and temperature. After obtaining color indices from photometry, mathematical regression using targets with known effective temperatures yields robust models [6-11].

3.2 Infrared Flux Method

The InfraRed Flux Method (IRFM) operates on the principle that stellar surface flux in the infrared is insensitive to temperature [12-13] and depends minimally on theoretical models, making it the method closest to the definition of effective temperature. This approach achieves temperature measurement precision of approximately 1-2% and can also determine stellar angular diameters.

3.3 Balmer Line Profile Fitting

Balmer lines exhibit strong coupling with effective temperature, and fitting their wings provides excellent temperature estimates. However, at higher temperatures (above 8000 K), the temperature-surface gravity coupling becomes strong, requiring complementary approaches for simultaneous determination [14-15].

3.4 Spectral Line Ratio Method

Different spectral lines show varying correlations with effective temperature, surface gravity, and metallicity—some positive, some negative, and with differing degrees of correlation. Reference [16] uses line depth ratios to determine temperature with precision reaching 10 K.

3.5 Line Index Method

This approach extracts line indices from spectra that correlate with atmospheric parameters to build mathematical models relating these indices to atmospheric parameters. The most widely applied is the Lick index proposed in [17], along with Rose indices [18], new Lick Balmer indices [19], and LICK/SDSS indices [20]. Reference [21] employs 322 equivalent width ratios for effective temperature estimation and over 100 Fe I line equivalent widths for metallicity estimation, achieving 74 K effective temperature precision and 0.07 dex metallicity precision when applied to FGK dwarfs and GK giants.

3.6 Metal Line Diagnostics Method

For high-resolution spectra, metal line diagnostics simultaneously solves for effective temperature, surface gravity, and microturbulence by combining ionization equilibrium and excitation equilibrium. Effective temperature is determined by requiring that abundances from Fe I lines show no dependence on excitation potential; surface gravity is set by enforcing consistency between Fe I and Fe II line abundances; and microturbulence velocity is determined by ensuring Fe I abundances are independent of equivalent width. Other element pairs such as Ti I/Ti II and Cr I/Cr II can also be used. This method requires auxiliary measurements of numerous metal line equivalent widths, often involving human-computer interaction and consuming considerable time, but yields high-precision results and remains a mainstream approach for high-resolution spectroscopy. The most representative software is MOOG, originally written in C by Sneden in 1973 [22], which has since been improved and integrated into various packages including FAMA [23], GAUFRE [24], MyGIsFOS [25], and iSpec [26].

3.7 Spectral Template Fitting

Spectral template fitting is currently a very common method, frequently serving as the initial step in parameter measurement, with more refined techniques like metal line diagnostics often using its results as starting values. This approach involves preprocessing the observed spectrum (continuum normalization, redshift removal, etc.), comparing it with theoretical spectral templates, and finding the best match, whose parameters are then assigned to the target spectrum. The method requires constructing a multi-dimensional spectral grid spanning various parameters including effective temperature, surface gravity, metallicity, and microturbulence. By utilizing complete spectral information, template fitting yields highly reliable results and is easily automated for application to massive spectroscopic datasets. The method must account for extinction-induced reddening of spectra. Algorithmic implementation focuses on optimizing grid precision and improving fitting speed and accuracy. Grid precision fundamentally determines final measurement accuracy—finer grids produce more accurate results but require more computational time.

Reference [3] discusses simultaneous parameter measurement using photometric and spectroscopic data and briefly analyzes limitations of the Radial Velocity Experiment (RAVE) spectral coverage for parameter estimation. Reference [27] combines spectral library grids with Bayesian models for application to Infrared Space Observatory short-wavelength spectrometer data. Reference [28] details the release of tens of thousands of spectra in RAVE' s second data release, describing the application of chi-squared minimization template matching based on theoretical spectral libraries for stellar parameter measurement. Reference [29] presents the SDSS-SEGUE Stellar Parameter Pipeline (SSPP), which integrates multiple methods including various line index techniques and chi-squared spectral fitting based on theoretical libraries.

ULYSS [30] employs ELODIE spectra [31] to perform multivariate high-order polynomial fitting for each pixel as a function of effective temperature, surface gravity, and metallicity, creating an empirical spectral grid capable of generating spectra for any stellar parameter combination; ULYSS also incorporates a point spread function to account for various line broadening effects. Software packages including GAUFRE [24], MyGIsFOS [25], and iSpec [26] all utilize spectral template fitting as their primary parameter measurement method. Reference [32] describes applications of the CFI and ULYSS codes to LAMOST [33] spectral atmospheric parameter measurement, comparing results with high-resolution spectroscopic parameters. Reference [34] introduces the Grid Search in Stellar Parameter (GSSP) software for medium-to-high resolution spectroscopy, compatible with various template libraries and offering specialized programs for binary star spectra. Reference [35] presents a polynomial fitting template grid constructed from the MILES empirical spectral library [36-37], applied to LAMOST spectra using chi-squared minimization and downhill algorithms for parameter measurement. Reference [38] applies the ROTFIT code to LAMOST-Kepler stars using the INDO-US spectral library [39], dividing spectra into eight segments for individual fitting before weighted summation to select the optimal template and output parameters. Reference [40] describes the APOGEE survey' s ASPCAP pipeline, which primarily uses chi-squared minimization based on theoretical spectral libraries to measure effective temperature, surface gravity, and metallicity.

Improving fitting speed and accuracy for a given grid represents another optimization direction. For example, Reference [41] investigates local grid multivariate linear regression, applying the MATISSE algorithm to GAIA [42] spectral data by performing a coarse global grid search followed by parameter optimization through projection onto specific vectors.

3.8 Machine Learning Methods

Machine learning studies how to simulate or implement human learning behavior using computational power to acquire new knowledge or skills. In stellar atmospheric parameter measurement, algorithms use stars with known parameters as training samples to learn from their observational data X and parameters Y (or regression information), then estimate parameters for new data. Compared to traditional parameter algorithms, machine learning offers higher efficiency, requires no predetermined mathematical model, involves minimal manual intervention, and can be applied to massive spectroscopic datasets.

Reference [43] tests artificial neural networks for spectral classification using multilayer backpropagation networks (MBPN). Reference [44] describes using Principal Component Analysis (PCA) for spectral dimensionality reduction followed by MBPN neural networks for parameter measurement, demonstrating that dimensionality reduction significantly decreases computational load while preserving accuracy. Reference [45] compares several machine learning methods for measuring atmospheric parameters from spectral indices, including the Minimum Distance Method (MDM), K-Nearest Neighbors (KNN), and Local Weighted Regression (LWR), along with their combinations with PCA dimensionality reduction, finding that LWR with PCA performs best. Reference [46] uses KNN to compare three input types—continuum-normalized spectra, line indices, and spectral lines—finding that line indices and spectral lines achieve similar precision, slightly higher than continuum-normalized spectra. Reference [47] employs genetic algorithms for spectral index selection combined with KNN for training and prediction, reducing program runtime while decreasing prediction errors by over 35%. Reference [48] applies feature extraction (absorption lines, emission lines, bands, continuum shape, spectral energy distribution inflection points) combined with Bayesian theory and classical statistics to classify FG-type stars from the Hamburg/ESO survey, achieving 400 K effective temperature precision and surface gravity and metallicity better than 0.68 dex for spectra with signal-to-noise ratios above 10. References [49-51] discuss various machine learning applications in large surveys such as GAIA. Reference [52] describes MBPN artificial neural networks for subdwarf classification. Reference [53] discusses AI techniques for low-resolution optical spectra and extends several neural network models as auxiliary methods. Reference [3] mentions using AI techniques like neural networks for "high-level" calibration from photometric and spectroscopic data to parameters. Reference [54] presents neural network applications to spectra from the 2.34-meter Vainu Bappu Telescope. Reference [55] investigates nonlinear regression models combined with PCA and wavelength range selection (WRS) dimensionality reduction for SDSS/SEGUE spectra. The SDSS parameter pipeline uses neural network algorithms, with tests demonstrating applicability to LAMOST spectral parameter measurement [56]. Reference [57] uses dereddened photometry from SDSS with KNN techniques to estimate stellar metallicity. Reference [58] applies PCA to ELODIE [31] and S4N spectral libraries for dimensionality reduction before constructing linear regressions for temperature, achieving 50 K internal error and comparing results with the infrared flux method. Reference [59] presents the Cannon code, which labels observational data with historically known parameters to build learning models for predicting unknown observations; testing on APOGEE data yields errors similar to APOGEE' s internal uncertainties [60]. Reference [61] uses kernel PCA and linear regression to measure atmospheric parameters and absolute magnitudes from LAMOST spectra. Reference [62] applies deep neural networks to SDSS spectra for stellar parameter measurement. Reference [63] uses the Cannon with APOGEE parameters and LAMOST spectra to measure parameters for 450,000 LAMOST giant spectra. Reference [64] employs the Cannon trained on APOGEE and K2/EPIC data to remeasure stellar parameters for the RAVE-on dataset.

Examining the evolution of stellar atmospheric parameter measurement methods reveals that as observational data quantity and variety increase, the utilized information expands from local features to full spectra, algorithmic complexity grows, and measurement precision improves. This trend reflects both enhanced astronomical data acquisition capabilities and substantially increased computational power recognized by the astronomical community, leading to widespread adoption of new technologies, software, and algorithms oriented toward big data [65-67]. Currently, the most widely applied algorithm is full-spectrum fitting, which requires extensive spectroscopic data and powerful computing capabilities to rapidly and accurately identify optimal matches from high-density, high-precision template grids for massive datasets. Machine learning, with its unique approach to data training and prediction, holds significant importance for astronomical research. For high-resolution, high-signal-to-noise spectra, metal line diagnostics remains highly regarded due to its exceptional precision, while infrared flux method results are commonly employed as reference standards.

Stellar research and atmospheric parameter measurement are critically important for understanding the formation and evolution of the universe. Consequently, improving measurement precision has long been a subject of intensive investigation. Stellar atmosphere parameters primarily include effective temperature (T_{eff}), surface gravity ($\log g$), metallicity ([Fe/H]), rotational velocity, microturbulence, and macroturbulence. While direct measurement is possible for only a handful of stars, indirect methods dominate, extracting parameters from multi-band photometry or spectroscopy. These can be broadly categorized into photometric methods, infrared flux method, Balmer line profile fitting, spectral line ratio methods, line index methods, metal line diagnostics, spectral template fitting, and machine learning methods. As a purely mathematical approach, machine learning' s widespread astronomical application has grown with the era of big data astronomy and dramatically increased computational power, encompassing and complementing previous astrophysical methods while gaining recognition for its efficiency and precision in massive data processing. Traditional methods such as metal line diagnostics and infrared flux methods remain prominent in high-resolution spectroscopy due to their high accuracy and stability.

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Note: Figure translations are in progress. See original paper for figures.