Stellar spectral template library construction based on generative adversarial networks

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ABSTRACT

Stellar spectral template libraries play an important role in the automated analysis of stellar spectra. Synthetic template libraries cover a very large parameter space but suffer from poor matching with observed spectra. In this study, we propose a synthetic-to-observed spectral translation (SOST) method based on generative adversarial networks. The SOST method is able to calibrate synthetic spectra by converting them to the corresponding observed spectra. We applied this method to Kurucz synthetic spectra and observed spectra data from the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST). After that, we constructed a stellar spectral library with uniform and broad parameter distributions using the SOST-corrected Kurucz synthetic spectra. Our stellar spectral template library contains 2431 spectra spanning a parameter space of 3500–8000 K for effective temperature (\(T_{\text{eff}}\)), 0.0–5.0 dex for surface gravity (\(\log g\)), and –2.0–0.5 dex for metallicity ([\(\text{Fe}/\text{H}\)]). The spectra in the library have a resolution of \(R \sim 1800\) and cover the wavelength range 3900–8700 Å. In order to verify the accuracy of this template library, we used the template library and the template-matching algorithm to derive the parameters of the PASTEL database. Compared to measurements using the original synthetic template library, the accuracies of the three parameters, \(T_{\text{eff}}\), \(\log g\), and [\(\text{Fe}/\text{H}\)], are improved, from 140 K, 0.31 dex, and 0.21 dex to 121 K, 0.26 dex, and 0.13 dex, respectively. In addition, we re-parameterised more than six million stellar spectra released by LAMOST DR8.

Key words. methods: data analysis – methods: statistical – techniques: spectroscopic – surveys – stars: fundamental parameters

1. Introduction

In recent years, an increasing number of large spectroscopic surveys have been started as well as completed. These surveys have generated an unprecedented number of spectra. For instance, the ongoing LAMOST Galactic Spectroscopic Survey of the Galactic Anti-centre (LSS-GAC) (Luo et al. 2015) has already collected millions of low-resolution (\(R \sim 1800\)) spectra of stars. Faced with massive amounts of stellar spectroscopic data, researchers need automated analysis tools to efficiently extract useful astrophysical information about target stars. The stellar spectral template library is able to perform analytical tasks by matching observed spectra with template spectra, such as classification of stellar types and determination of stellar atmospheric parameters. These pieces of information are essential for understanding the formation, structure, and evolution of the Milky Way (Jofré et al. 2019). Several stellar parameter pipelines, such as SSPP (Lee et al. 2008), LASP (Luo et al. 2015), and LSP3 (Xiang et al. 2015), have emerged to provide convenient solutions for spectral parameter determinations. These mainstream parametric measurement pipelines rely on synthetic template libraries or empirical template libraries; however, they all have corresponding shortcomings.

The synthetic template libraries comprise stellar spectra generated by theoretical models based on stellar properties. The synthetic template libraries offer noiseless data covering a wide range of stellar parameter values. In a related work on template library construction based on LAMOST data, it has been pointed out that the influence of theoretical and instrumental factors could lead to inconsistencies between the synthetic model and observed spectra at the wavelengths of some features (Du et al. 2019). This mismatch may lead to unrealistic parameter measurements. On the theoretical side, the parameters that have been considered during spectral modelling are not comprehensive, as they lack factors such as microturbulence, rotation velocities, and convection. Assumptions regarding the physics of stellar models both in their interiors and atmospheres also impact the accuracy of any synthetic grid. These theoretical limitations have been mentioned in previous studies (Kurucz 2013; Prieto et al. 2018; Franchini et al. 2018). On the instrumental side, the modellings of instrumental factors and noise lacks perfection (Ballester et al. 2000; Martioli et al. 2012).

The empirical template libraries such as MILES (Sánchez-Blázquez et al. 2006; Falcón-Barroso et al. 2011) and ELODIE (Prugniel & Soubiran 2001; Prugniel et al. 2007) consist of high-quality, real observed spectra with stellar atmospheric parameters (Du et al. 2019; Royer et al. 2024; Prieto et al. 2004; Verro et al. 2022), having been created through the efforts of observers. However, a good empirical template library requires coverage of a wide range of parameters, and acquiring

* The source code and pre-trained models are available at https://github.com/zeyangyan/SOST
observed spectra that satisfy this requirement is a challenging task. Furthermore, the stellar labels determined using empirical template libraries are limited in accuracy. This is due to the errors present in the parameter labelling of the observed spectra, which are passed on to the spectra to be measured during the parameter measurement. Jofré et al. (2019) reviewed the latest efforts in this field (Ren et al. 2016; Jönsson et al. 2018) in order to assess the accuracy of stellar parameter measurement results and discussed the uncertainties of the measurement results from the perspectives of random uncertainties, systematic uncertainties, and biases.

Some works have been done by researchers to overcome the shortcomings of the current synthetic spectra. Works using traditional methods typically attempt to take into account a variety of complex physical effects and data properties when modelling spectra. Kovalev et al. (2019) incorporated non-local thermodynamic equilibrium (NLTE) effects into the model atmospheres when determining stellar parameters and abundances in medium-resolution spectra of FGK-type stars. Similarly, Amarsi (2016) investigated the departure from local thermodynamic equilibrium (LTE) of atomic oxygen and its impact on various oxygen lines in FGK-type stars, offering grids predicting 3D NLTE-based equivalent widths and abundance corrections. Additionally, Bialek et al. (2020) bridged the synthetic gap by augmenting the synthetic spectra with real observational features, such as by adding Gaussian noise, applying rotational and radial velocities, removing the continuum, and masking geodesic regions. However, these methods usually require a great deal of a priori knowledge and manual adjustments, and it is difficult for them to model the various effects in the spectra, which tend to overlook certain details or effects.

Compared with traditional methods, deep learning methods have stronger non-linear modelling capabilities and are able to learn features and laws automatically without many manual adjustments. Deep learning technologies, including neural networks, convolutional neural networks (CNNs), and generative adversarial networks (GANs), are widely utilised in astronomy, particularly in spectral analysis. Recent studies have introduced innovative algorithms, such as ZETA-PAYNE by Straunil et al. (2022), that use CNNs to accurately analyse spectra from hot OB-type stars in SDSS-V data. Additionally, Gebran et al. (2022) have demonstrated the effectiveness of CNNs in determining stellar parameters from observed and synthetic spectra, offering practical guidance for their application in astronomy. Furthermore, deep learning techniques, such as LSTM neural networks, have been employed in studies, including that of Hu et al. (2022), to analyse spectral time series of Type Ia supernovae, enabling precise reconstruction of spectral sequences from a single observed spectrum. In response to the small number of O-type stars in the LAMOST data release, Zheng et al. (2020) proposed the SGAN for generating artificial O-type spectra. O’Briain et al. (2021) proposed Cycle-STARNet, a domain-adaptive method to narrow down the discrepancy between synthetic spectra and observed spectra. Gebran (2024) established a connection between stellar parameters and spectra by training a fully connected neural network, which can be used for library construction. Nevertheless, the reduction of the mismatch between the synthetic model and observed spectra is worth exploring.

In this paper, we propose a synthetic-to-observed spectral translation method called SOST. This method is based on a GAN and uses Kurucz synthetic spectra\footnote{The instructions for using the Kurucz model can be found at the following URL: \url{http://kurucz.harvard.edu/programs.html}} (Castelli 2005) (Kurucz model atmospheres with the radiative code SYNTHE) and LAMOST observed spectra as data sources. The well-trained SOST method can guide the calibration of synthetic spectra by providing observed spectra and correct errors that may arise during the synthetic spectrum modelling process. The SOST-corrected synthetic spectra can achieve a favourable match with the observed spectra. This addresses the past shortcomings of relying on either synthetic spectra or observed spectra data.

Additionally, we construct a stellar spectral template library using the SOST method. Our spectral library offers a set of stellar spectra with uniformly and extensively distributed parameters. The effective temperature ($T_{\text{eff}}$) ranges from 3500 to 8000 K, the surface gravity ($\log g$) spans 0.0–5.0 dex, and the metallicity ([Fe/H]) varies from $-2.0$ to 0.5 dex. The wavelength coverage for the templates spans 3900–8700 Å at a resolution of approximately $R = 1800$. To assess the accuracy of our constructed library, this study employs a template-matching method based on $\chi^2$ minimisation (Jofré et al. 2010) to compare the parameters obtained using SOST with measurements from PASTEL (Soubiran et al. 2016) and the Large Sky Area Multi-Object Fibre Spectroscopic Telescope Data Release 8 (LAMOST DR8; Yan et al. 2022). The template-matching method determines the parameters by comparing the target spectrum with the template spectrum (Zwitter et al. 2008; Lee et al. 2008). Through comparison with external databases, the accuracy of this template was determined to be 121 K, 0.26 dex, and 0.13 dex for $T_{\text{eff}}$, log $g$, and [Fe/H], respectively. This work provides a powerful support for stellar studies and a powerful tool for a deeper understanding of stars in the Universe (Suda et al. 2008; Yoon et al. 2018).

This paper is organised as follows: the SOST and the stellar spectral template library construction method are introduced in Sect. 2. The spectral data used for the experiments as well as the designed experiments for stellar spectral parameter determinations are described in detail in Sect. 3. Finally, we summarise this work in Sect. 4.
Fig. 1. Architecture of SOST. The style encoder utilizes strided convolutional layers followed by a global average pooling layer and a fully connected layer. In contrast, the content encoder employs strided convolutional layers alongside residual blocks. In the decoder, a multi-layer perceptron is employed to compute a set of AdaIN parameters based on the style code. Subsequently, the content code is processed through residual blocks with AdaIN layers to achieve cross-domain spectral translation.

The generation of spectra is countered by a discriminator that evaluates the quality of the generated spectra. The method is based on MUNIT (Huang et al. 2018). MUNIT constructs a multi-modal unsupervised image translation framework that is capable of transforming images across different seasons while maintaining photo content. Similarly, in our spectral calibration, robust spectral features correspond to content features in photo images, while the calibration of synthetic spectra factors correspond to style features, akin to seasons in photo images.

In order to adapt MUNIT to the spectral generation work, we modified its internal network structure (convolutional as well as normalisation methods, etc.), and added cycle consistency loss so that the method is applicable to domains between the observed spectra of LAMOST and the synthetic spectra of the Kurucz synthetic spectra transfer learning. The components of the SOST are briefly described in this subsection, and the functions of each component and the training process of the method are described in detail in Sect. 2.2.

2.2. Architecture and training

In order to achieve domain transfer between spectra while ensuring that the generated spectra do not lose their own information, we designed multiple loss functions to constrain the training process. We used spectral reconstruction loss (Eq. (3)) and cross-domain feature reconstruction loss (Eqs. (4) and (5)) to train the auto-encoder for feature extraction and reduction. We used cycle consistency loss (Eq. (6)) to constrain the generated spectra and generative adversarial loss (Eq. (7)) to train the antagonism between the generated spectra and the real spectra so that the distribution of the cross-domain spectra matches the distribution of the target spectra. The guidance of the method during
training was achieved through these loss functions. In the following section, we provide a detailed explanation of the components of Eq. (2). The overall loss during training is as follows:

\[
\mathcal{L} = \lambda_{GAN}(\mathcal{L}_{GAN}^{\text{synth}} + \mathcal{L}_{GAN}^{\text{obs}}) + \lambda_{id}(\mathcal{L}_{id}^{\text{synth}} + \mathcal{L}_{id}^{\text{obs}}) + \lambda_{cont}(\mathcal{L}_{cont}^{\text{synth}} + \mathcal{L}_{cont}^{\text{obs}}) + \lambda_{style}(\mathcal{L}_{style}^{\text{synth}} + \mathcal{L}_{style}^{\text{obs}}),
\]

(2)

where the weights \(\lambda_{GAN}\), \(\lambda_{id}\), \(\lambda_{cont}\), and \(\lambda_{style}\) are hyperparameters that control the importance of each part of the loss function. The individual loss functions are described in detail in the following subsections. After conducting several empirical tests, we found that setting \(\lambda_{GAN} = 1\), \(\lambda_{id} = 10\), \(\lambda_{cont} = 1\), and \(\lambda_{style} = 1\) resulted in satisfactory performance.

### 2.2.1. In-domain spectra reconstruction loss

The encoder-decoders should be able to map spectra to latent representations and then back to original spectra within each domain. This process enables the auto-encoder model to learn both the feature extraction and generative capabilities of spectra. As shown in Fig. 2, \(E^c\) and \(E^s\) compress the data from the high-dimensional space to the potential space, and generator \(G\) does the opposite; that is, it converts the potential space back to the high-dimensional space. The encoder and generator pairs that are inverse to each other are learned by minimising the difference between the reconstructed spectrum and the input spectrum. In the next step, the learned encoder and generator pairs can be used for feature extraction and restoration of the spectral data. Equation (3) demonstrates the detailed process of in-domain spectra reconstruction, which involves feature extraction by the encoder followed by reconstruction through the generator and computing the L1 loss with the original spectrum. The loss within the synthetic spectra domain can be written as

\[
\mathcal{L}_{\text{recon}}^{\text{synth}} = \mathbb{E}_{X_{\text{synth}} \sim p(X_{\text{synth}})} \left[ \left\| G_{\text{synth}}(E^c_{\text{synth}}(X_{\text{synth}}), E^s_{\text{synth}}(X_{\text{synth}})) - X_{\text{synth}} \right\|_1 \right],
\]

(3)

where \(X_{\text{synth}}\) is the synthetic spectrum sampled from the distribution of synthetic spectra \(p(X_{\text{synth}})\) and \(E^c_{\text{synth}}\), \(E^s_{\text{synth}}\), and \(G_{\text{synth}}\) are the content encoder, style encoder, and generator within the synthetic spectra domain, respectively. The L1 loss (mean absolute error) is utilised to compute the loss function.

### 2.2.2. Cross-domain feature reconstruction loss

For the content and style features obtained from sampling during cross-domain translation, we wanted to be able to reconstruct them after generating the cross-domain transfer spectra (generated by combining features across domains) by encoding them again as shown in Fig. 3. Reconstruction of features ensures that the encoder is able to extract the content features of the shared latent space and the style features of the unique latent space, which is consistent with the hypothesis presented at the beginning of this section. Instead of using observed spectra for style feature extraction during training, we directly adopted the standard Gaussian distribution as the prior distribution. This constraint ensures that the style potential space is regularised, which helps generate diverse spectra when transferring across domains. Our goal is that synthetic spectra can be generated diversely by different features provided by different observed spectra rather than through a simple one-to-one correspondence between synthetic and observed spectra. Equations (4) and (5) show the process of the generator generating spectra in the cross-domain followed by feature extraction by the encoder and computing the L1 loss with the input features. The cross-domain feature reconstruction can be achieved according to the following equation:

\[
\mathcal{L}_{\text{recon}}^{\text{obs}} = \mathbb{E}_{X_{\text{obs}} \sim p(X_{\text{obs}}), s_{\text{obs}} \sim q(s_{\text{obs}})} \left[ \left\| E^c_{\text{obs}}(G_{\text{obs}}(c_{\text{synth}}, s_{\text{obs}}) - c_{\text{synth}}) \right\|_1 \right],
\]

(4)

\[
\mathcal{L}_{\text{recon}}^{\text{synth}} = \mathbb{E}_{X_{\text{synth}} \sim p(X_{\text{synth}}), s_{\text{obs}} \sim q(s_{\text{obs}})} \left[ \left\| E^c_{\text{obs}}(G_{\text{obs}}(c_{\text{synth}}, s_{\text{obs}}) - s_{\text{obs}}) \right\|_1 \right],
\]

(5)

where \(c_{\text{synth}}\) and \(s_{\text{obs}}\) are the content code in the synthetic spectra domain and the style code in the observed spectra domain, respectively. The value of \(p(c_{\text{synth}})\) is given by \(E^c_{\text{synth}}(X_{\text{synth}})\), and \(q(s_{\text{obs}})\) is the prior \(N(0, 1)\).
Cycle consistency loss for synthetic spectra can be written as the difference between the generated synthetic spectra and the original synthetic spectra. The cycle consistency loss for synthetic spectra, which enhances the robustness and interpretability of the model. Equation (6) is the L1 loss between the cycle reconstruction of the synthetic spectrum, it will be difficult to return to the original domain by reverse conversion. This two-way conversion constraint ensures that the generated spectra are associated with the original input spectra, which enhances the robustness and interpretability of the model. Equation (6) is the L1 loss between the cycle reconstructed synthetic spectra and the original synthetic spectra. The cycle consistency loss for synthetic spectra can be written as

\[ L_{cy}^{synth} = \mathbb{E}_{X_{synth} \sim p(X_{synth})} [ \| G_{synth}(E_{obs}(X_{synth} \rightarrow obs), E_{synth}(X_{synth})) - X_{synth} \|_1 ], \]

where \( X_{synth \rightarrow obs} \) is the synthetic spectrum transformed across domains to the observed spectral domain, which is the main focus of this paper. The value of \( p(X_{synth \rightarrow obs}) \) is given by \( G_{obs}(c_{synth}, c_{obs}) \).

2.2.4. Generative adversarial loss

The method, in addition to the auto-encoder model mentioned above, includes the discriminator model, as shown in Fig. 5, and the two parts are trained alternately to form the GAN together. The goal of the GAN is for the generator to produce spectra that are sufficient to deceive the discriminator. We wanted the spectra transferred across domains to have the same data distribution as the spectra in the target domain, which requires matching the distribution of the synthetic spectra with the distribution of the observed spectra. In order to generate better spectral data, a matching exercise between the synthetic spectra and the observed spectra is required. The matched observed spectra will be a better guide for the transfer of the synthetic spectra across domains. Here, the matching was done by minimising the \( \chi^2 \) distance. We defined \( \chi^2 \) as follows:

\[ \chi^2 = \sum_{i} \frac{(S^i - O^i)^2}{\sigma^2} , \]

where \( S^i \) and \( O^i \) are the flux densities of the synthetic spectra and the observed spectra of the ith pixel, respectively. The term \( N \) is the total number of pixels used to calculate the \( \chi^2 \) distance.
3. Experiments and results

In this section, we first detail how the calibration of the synthetic spectra is achieved, including the construction of the experimental dataset and the pre-processing procedure. Then we perform in-domain reconstruction, cross-domain translation, and t-SNE visualisation of the test set spectra to validate the SOST. In-domain reconstruction refers to the reduction of the test set spectra within the original spectral domain, which helps validate the performance of the method in the same spectral domain and is also a prerequisite for cross-domain translation. We also used the t-SNE visualisation method to clearly demonstrate the distribution of the synthetic spectra and observed spectra as well as the features extracted from them before and after the cross-domain translation. The visualisation enables the changes in the spectral distribution to be observed intuitively, further demonstrating the good performance of the method in the spectral domain transfer task.

However, good visualisation results do not guarantee that the spectra generated by the SOST correctly correspond to the parameters. Thus, in conclusion, we constructed a stellar spectral template library using the SOST and then estimated the parameters for the PASTEL catalogue and the observed spectra released by LAMOST DR8 (Yan et al. 2022), respectively. Through this experiment, the usefulness and reliability of the SOST in practical parameter measurement tasks were successfully demonstrated. This series of experiments provides a solid experimental foundation for our research and an important reference and tool for further research in the field of spectral generation and parameter determinations.

3.1. Calibration of synthetic spectra

In this section, we detail the experimental setup as well as the in-domain reconstruction, cross-domain transfer, and t-SNE visualisation of the domain distribution experiments. We show how SOST can compensate for the difference in the synthetic spectra with respect to the observed spectra, also known as the synthetic gap.

3.1.1. Experimental setup

The source of the observed spectra is the eighth data release of the LAMOST low-resolution spectral survey. To ensure the quality of the spectral data as well as a wider and uniform parameter distribution, we sampled the spectra according to the stratified sampling of the officially provided atmospheric parameters. We selected 50,000 spectra of the training set, 5000 spectra of the validation set, and 5000 spectra of the test set with an S/N greater than 30 in the $g$ band. The source of the synthetic spectra is the Kurucz synthetic template library, and the parameter coverage of these synthetic spectra is $3500 \, K \leq T_{\text{eff}} \leq 8000 \, K$, in steps of 250 K; 0.0 dex $\leq \log g \leq 5.0$ dex, in steps of 0.5 dex; and $-2.5 \, \text{dex} \leq \Delta [\text{Fe/H}] \leq 0.5$ dex, in steps of 0.25 dex. For generating the Kurucz synthetic templates used in our study, we utilised the Kurucz spectral synthesis code based on the ATLAS stellar atmosphere models provided by Sbordone et al. (2004). The initial resolution of the synthetic data is 2000. To match the resolution of the LAMOST low-resolution spectra (1800), we smoothed the synthetic spectra using fast Fourier transform convolution with a Gaussian kernel (Zhang et al. 2020).

Although the Kurucz synthetic template library covers a wide range of parameters, their parameter distributions are relatively sparse, and generating synthetic spectra is relatively time-consuming. Ting et al. (2019) have demonstrated that the PAYNE model based on residual networks exhibits strong fitting capabilities, providing a good connection between physical parameters and synthetic spectra. To ensure consistency with the parameter space of observed spectra, we trained the PAYNE model using the Kurucz synthetic spectral template library. The well-trained PAYNE model generated synthetic spectral datasets that match the parameter distribution of observed spectra. In this way, datasets of synthetic and observed spectra with consistent parameter distributions were obtained.

Next, we employed linear interpolation to interpolate the synthetic spectra and observed spectra onto the same wavelength grid, ensuring they are aligned in the same positions. The covered wavelength range extended from 3900 Å to 8700 Å, with a sampling of 1 Å per pixel. For the fluxes, we performed pseudo-continuum spectral normalisation (Zhang et al. 2020, 2021; Cai et al. 2022, 2024). This removed the dispersion effect between the spectra and highlighted the chemical features, which helps when comparing and analysing the spectral features of the stars in order to study their physical properties and chemical composition. These steps play a key role in the pre-processing of spectral data.

3.1.2. Reconstruction of synthetic spectra

As discussed in Sect. 2.2.1, SOST performs spectral reconstruction during training. We first show in this section that in-domain reconstruction is valid with cycle reconstruction, which is necessary for cross-domain translation.

The validity of the in-domain reconstruction and the cycle reconstruction is demonstrated in Fig. 7. The blue end of the

Fig. 7. In-domain reconstruction and cycle reconstruction. This figure shows the residuals between the 5000 synthetic spectra in the test set and themselves after in-domain reconstruction and cycle reconstruction. These spectra cover most of the stellar parameter range. The blue part indicates the residuals after reconstruction of each spectrum in the wavelength range 4000–5500 Å. The colour depth is positively correlated with the number of spectra in this error. The red line in the figure indicates the average residuals, and the orange line indicates the average absolute residuals. The upper panel shows the in-domain reconstruction residuals as the relative residuals between $X_{\text{synth}} \rightarrow X_{\text{synth}}$ and the original spectra $X_{\text{synth}}$, and the lower panel shows the cycle reconstruction residuals as the relative residuals between the spectra $X_{\text{synth}} \rightarrow X_{\text{obs}} \rightarrow X_{\text{synth}}$ and the original spectra $X_{\text{synth}}$. The residuals for both the in-domain and cycle reconstructions are very small and can be neglected, as can be seen in the figure.

The phenomenon of having more residual values (exceeding one standard deviation) at certain positions of emission lines and absorption lines, such as the Balmer H$\beta$ line, G-line, and MgI line, does exist. The reasons for these variations remain unclear, and the complex variations of emission lines and absorption lines in the spectra may be one factor.

3.1.3. Visualisation of domain distribution using t-SNE

In this section, we use the method introduced in Sect. 2.3 to pair the synthetic and observed spectra in the test set. The matched spectral pairs are fed into the encoder in the SOST for feature extraction. The synthetic spectra provide content features, the observed spectra provide style features, and the two features are combined to achieve domain transfer from the Kurucz synthetic spectra to the LAMOST observed spectra. The t-SNE (Van der Maaten & Hinton 2008) is a non-linear dimensionality reduction and data visualisation algorithm that maps high-dimensional data onto a low-dimensional space in order to be able to better present the similarities and differences between the data. We used t-SNE to visualise the cross-domain translation process.
3.2. Estimation of stellar spectral parameters

In previous experiments, the successful transfer of the synthetic spectra across domains was demonstrated by t-SNE visualisation. In this section, we explore the effect of the corrected synthetic spectra on parameter estimation. In this experiment, template spectra were generated using SOST and parameter estimation was performed using a method based on $\chi^2$ minimization for template-matching. The estimated parameters were compared with the stellar atmospheric parameters published by the PASTEL database and LAMOST DR8. Different spectroscopic surveys usually employ different spectral analysis methods to obtain the stellar atmospheric parameters and chemical compositions and to compare them with different spectroscopic surveys in order to assess the reliability of the generated spectra (Kassounian et al. 2019).

3.2.1. Stellar spectral template library construction

We used the low-resolution A, F, G, and K type stellar parameter catalogues published by LAMOST as a reference. Grids were constructed with a range of steps of 150 K, 0.25 dex, and 0.15 dex between the $T_{\text{eff}}$ of 3500–8000 K, $\log g$ of 0.0–5.0 dex, and [Fe/H] of −2.0–0.5 dex, respectively. In order to minimise the effect of LASP measurement errors, we expelled grids with fewer than five stars. A stellar parameter was randomly selected as the parameter of the template spectra within the grid, and a uniform and wide-coverage parameter distribution was ultimately constructed. The metallicity considered in our study is [Fe/H], which is consistent with the official data from LAMOST. We generated synthetic spectra corresponding to this parameter distribution using the PAYNE model. The pairs of synthetic spectra and observed spectra were then matched by the $\chi^2$ distance. Our test set included a wide range of atmospheric parameters, and to reduce the computational effort, we used the data from the test set directly for matching. The synthetic spectra were then transferred across domains to observed spectra using the SOST, where the spectral atmospheric parameter values after the cross-domain translation were inherited from the synthetic spectra. The corrected synthetic spectra form a stellar spectral template library with a broad and uniform distribution of stellar parameters. The stellar spectral template library contains 2413 spectra, and the spectra in the library have a resolution of $R \sim 1800$ covering the wavelength range 3900–8700 Å.

Our method has several advantages over previous methods of constructing synthetic template libraries and empirical template libraries. Firstly, the introduction of the PAYNE model made it easy for us to generate synthetic spectra data with any parameter. Second, the SOST better enables correction of the synthetic spectra, overcomes the synthetic gap, and does not require the a priori knowledge of the atmospheric parameters of the observed spectra. Finally, the advantages based on the first two points allowed us to easily construct a stellar spectral template library with a wider parameter coverage and more uniform parameter distributions.

The atmospheric parameter distributions of the ELODIE (Wu et al. 2011) library, which LASP derives stellar atmospheric parameters, and the SOST spectral library are shown in Fig. 9. As can be seen from the figure, our constructed stellar spectral template library has a wider parameter coverage and more uniform parameter distribution. The influence of clusters and observed spectra pairs after the cross-domain translation to two dimensions using t-SNE, respectively. In the upper-left panel, one can see that there is a more significant difference between the synthetic spectra and the observed spectra. This is the synthetic gap mentioned earlier, which is the gap we aim to overcome. The upper-right panel shows the common content features extracted by the content encoder. The lower-left panel shows that the style encoder extracts the style features of each of the two domains, which matches our hypothesis. The lower-right panel shows that the data distributions of the two domains are mixed together after the cross-domain translation, which proves that SOST overcomes the differences between the two domains better.
and vacancies on the parameter distribution of the traditional empirical template libraries of the measurement results has been overcome. Figure 10 shows some samples of SOST spectral templates. All spectra in the SOST spectral templates are normalised by pseudo-continuum normalisation. For spectra with [Fe/H] greater than 0.3, the absorption lines appear deeper. Next, we use the SOST spectral library for parameter estimation in order to further demonstrate the validity of this stellar spectral template library.

3.2.2. Accuracy assessment by the PASTEL database

PASTEL is a database of stellar atmospheric parameters brought together from multiple sources. The parameters it provides are obtained from detailed analyses of high-resolution high-S/N spectra, thus providing more accurate measurements, and are often used to assess the accuracy of parameter measurements. In this study, the first step to assessing our obtained parameters was to remove the null values of the parameters in the PASTEL...
Fig. 11. Comparisons of the results of parameter measurements using the Kurucz and SOST spectra libraries with the PASTEL database. The figure shows the comparison of the parameters $T_{\text{eff}}$, $\log g$, and [Fe/H] from left to right. The samples are colour-coded according to their density. In the top row, the horizontal coordinates are the measurements provided by the PASTEL database, the vertical coordinates are the measurements from the Kurucz spectra library, and the diagonal dashed line is the reference line. The bias and scatter of the samples are labelled in the upper-left corner of the picture in the upper panel. In the bottom row, the vertical coordinates represent the results of the measurements using the SOST spectra library. As is shown, a lower bias and scatter are obtained when using the SOST spectra library compared to PASTEL database.

Fig. 12. Comparison of our results with the parameters of LAMOST DR8. A total of 6,542,528 spectral data were compared.

database. Then, a cross-match with the low-resolution spectral data from the eighth LAMOST release was performed with a matching radius of 3 arcsec. Stars with $T_{\text{eff}}$ between 3500 K and 8000 K were selected. Finally, for $T_{\text{eff}}$, $\log g$, and [Fe/H], 2190, 1872, and 1837 samples that can be compared were obtained.

In this subsection, we use the template spectral before and after the SOST correction to parameterise the observed spectra in the PASTEL database. Typically, one assesses the quality of the predictions using the deviation and scatter between the predictions and the labels of the stars. Good predictions usually have a low bias and scatter. Importantly, the bias quantifies the accuracy, whereas the scatter quantifies the precision of the method.

As can be seen in Fig. 11, after SOST correction, the predictions of the stellar atmospheric parameters $T_{\text{eff}}$, $\log g$, and [Fe/H] show a significant improvement. The bias decreases from 144 K, −0.08 dex, and −0.33 dex before correction to −20 K, −0.01 dex, and 0 dex, respectively, while the dispersion decreases from 140 K, 0.31 dex, and 0.21 dex to 121 K, 0.26 dex, and 0.13 dex, respectively, before correction. The significant improvement of these metrics suggests that the SOST-corrected spectra are closer to the observed spectra, and therefore more accurate measurements of stellar parameters can be obtained. This further demonstrates the effectiveness of the SOST construction template library.

3.2.3. Comparison with the results of the LAMOST DR8 data survey

LAMOST DR8 is the eighth data release of LAMOST, a large sky area multi-object fibre-optic spectroscopic telescope developed by China for large-scale spectroscopic surveys. LAMOST uses LASP to estimate the $T_{\text{eff}}$, $\log g$, [Fe/H], and other parameters of stars. In our study, we selected a total of 6,542,528 spectral data in the $T_{\text{eff}}$ range of 3500–8000 K for parameter measurements and compared the results with those released by LAMOST DR8. Subsequently, we utilised a template-matching method based on $\chi^2$ minimisation, using the SOST spectral library, to derive the stellar parameters of the LAMOST DR8 data. This method selects two templates with the minimum $\chi^2$ for the target spectrum, assigns weights based on their $\chi^2$ distances, and then calculates the weighted average as the measurement result. From Fig. 12, it can be seen that compared with the parametric results published by LAMOST DR8, our results have a measurement deviation of $-40 \pm 121$ K for $T_{\text{eff}}$, $-0.05 \pm 0.22$ dex for $\log g$, and $-0.01 \pm 0.16$ dex for [Fe/H]. Overall, our
results are in good agreement with the parameter results published by LAMOST DR8, indicating that the template library we constructed achieves satisfactory results in stellar parameter measurements.

The relationship between the parameter difference and S/N of the measurements using the SOST and LAMOST DR8 is shown in Fig. 13. We chose spectra with S/N between 6 and 250. This choice was due to the fact that the small number of spectra with S/N greater than 250 lose statistical significance. From the figure, it can be seen that with the increase in S/N, the deviation and scatter of our predictions from the LASP residuals do not change significantly, and they still agree more closely with the LASP results. When the S/N is low (less than ten), the accuracy of the corresponding three parameters is 130.04 K, 0.24 dex, and 0.17 dex. The accuracy of the three parameters decreases to 118.42 K, 0.21 dex, and 0.15 dex when the S/N is high (greater than 200), and the accuracy of the measurement results is further improved with the increase of the S/N.

To further examine the differences between the SOST measurements and the parameters of LAMOST DR8, in Fig. 14 we mesh the $T_{\text{eff}}$, $\log g$, and [Fe/H] parameter measurements released by LAMOST DR8. Specifically, we meshed in steps of 400 K and 0.5 dex in the region where $T_{\text{eff}}$ ranges from 3500 to 8000 K and $\log g$ ranges from 0 to 5 dex. For [Fe/H], we divided it into the following ranges: $[-3.0, -1.5]$; $[-1.5, -0.6]$; $[-0.6, -0.2]$; $[-0.2, 0.2]$; and $[0.2, 1.0]$. In each grid, the difference between the SOST measurements and the LAMOST DR8 parameters was calculated, summed, and divided by the number of spectra to obtain the mean value. The following can be observed from Fig. 14. For stars with higher $T_{\text{eff}}$ (>6700 K), our estimates show differences in temperature compared to those published by LAMOST. The LASP provides higher values of the $T_{\text{eff}}$ for hot stars compared to our results. Ren et al. (2016) pointed out that there is a systematic overestimation of $T_{\text{eff}}$ measurements for stars at higher temperatures on external calibration of LASP atmospheric parameters. This discrepancy is consistent with our results. For stars with $\log g$ less than two, our SOST method gives lower values compared to LASP, and the difference is more pronounced. This discrepancy may be due to the small number of stars with $\log g$ less than two in ELODIE and the template library used by LASP, which leads to the deviation of the results (Chen et al. 2022). For stars with [Fe/H] in the range $[-3.0, -1.5]$, our SOST method generally gives higher values, and the differences are more pronounced. This may be due to limitations in the parameter coverage of spectral data currently released using LAMOST DR8. Our template library lacks adequate coverage of low-metallicity stars, causing the results to be pulled towards more metal-abundant quantities during template matching.

Taken together, our measurements differ in some cases from the parameters of LAMOST DR8, and these differences may be influenced by the coverage of the template library and stellar properties. It is important to note that despite the differences, our estimates still show some degree of agreement with the atmospheric parameters published by LAMOST.

4. Conclusions

In traditional stellar spectral template library construction efforts, the construction is usually based on observed spectra or synthetic spectra. We have proposed a template library construction method, called SOST, that is different from previous methods. This method is based on a GAN and uses an autoencoder to separate and recombine the content and style features of spectra. The content features of synthetic spectra are cross-domain combined with the style features of observed spectra, achieving a cross-domain transfer of synthetic spectra. This process accomplishes the correction of synthetic spectra, and the corrected synthetic spectra can have a good match with the observed spectra that are to be measured. The distinctive feature of this method lies in its elimination of the need for spectral expertise and manual feature extraction.

With this approach, we calibrated the Kurucz synthetic spectra using LAMOST observed spectra, which in turn led to
Fig. 14. Distribution of the mean value of the difference between our results and the parameters of LAMOST DR8 in the $T_{\text{eff}}$–$\log g$ plane. The three columns of subplots in the figure are the $T_{\text{eff}}$ difference, the $\log g$ difference, and the [Fe/H] difference (from left to right), and the four rows are the different [Fe/H] ranges (from top to bottom): $[-3.0, -1.5)$, $[-1.5, -0.6)$, $[-0.6, -0.2)$, $[-0.2, 0.2)$, and $[0.2, 1.0]$. Each dot in the figure represents the mean value obtained by summing the parameter difference of a grid with a $T_{\text{eff}}$ of 400 K and a $\log g$ of 0.5 dex size range and dividing it by the number of spectra, with the size of the dots representing the size of the difference, where red means that our results are larger than those published in LAMOST DR8 and blue means the opposite.

the construction of a widely distributed and uniform template library of stellar spectra. The template library includes a total of 2413 spectra. It covers a parameter space ranging from 3500 to 8000 K for effective temperature, 0.0 to 5.0 dex for surface gravity, and –2.0 to 0.5 dex for metallicity, while $T_{\text{eff}}$, $\log g$, and [Fe/H] were constructed in grids with step ranges of 150 K, 0.25 dex, and 0.15 dex, respectively. We used the library to perform parameter measurements of the PASTEL database, and after method correction, the accuracy of the predictions of the atmospheric parameters $T_{\text{eff}}$, $\log g$, and [Fe/H] was significantly improved, decreasing from 140 K, 0.31 dex, and 0.21 dex to 121 K, 0.26 dex, and 0.13 dex. Finally, we also used our stellar spectral template library to estimate the atmospheric parameters of more than 6.5 million spectral data released by LAMOST DR8.

The automatic calibration principle of SOST is versatile and can be applied to reduce discrepancies among various astronomical projects. Moreover, we plan to explore its applicability to various astronomical projects. The work in constructing the template library contributes to stellar parameter measurements, establishing a solid foundation for future studies on the stellar populations, kinematics, and chemistry of the Galactic disc, along with its evolutionary history. Our results further demonstrate the significance of deep learning in advancing astronomical techniques.

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Appendix A: SOST architecture

Here, we summarise the detailed architecture of each sub-module of SOST in Table A.1. Each row represents the operations applied by each network layer, including convolution, normalisation, and activation functions. The CONV layer denotes a standard 1D convolutional layer; the DCONV layer represents a transposed convolutional layer; FC stands for a fully connected layer; IN stands for InstanceNorm1d; ReLU and LeakyReLU are used as activation functions; InstanceNorm1d and AdaIN are used for normalisation; AdaptiveAvgPool1d and AvgPool1d layer denote a pooling layer. For each layer, N, K, S, and P represent the number of filters, the size of the filter kernel, the stride of the convolution operation, and the size of the padding for the convolution operation, respectively. The input spectrum has 4800 pixels. After dimensionality reduction by the encoder, the content code dimension was $256 \times 298$, while the style code dimension was $8 \times 1$.

Table A.1. Detailed architecture of the SOST sub-module.

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<tr>
<th>Layer</th>
<th>Content_Encoder_Down – sampling</th>
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<tbody>
<tr>
<td>1</td>
<td>CONV – (N64, K7, S4), IN(N64), ReLU</td>
</tr>
<tr>
<td>2</td>
<td>CONV – (N128, K4, S2), IN(N128), ReLU</td>
</tr>
<tr>
<td>3</td>
<td>CONV – (N256, K4, S2), IN(N256), ReLU</td>
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<th>Layer</th>
<th>ResidualBlock</th>
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<tr>
<td>2</td>
<td>CONV – (N256, K7, S1, P3), IN(N256)</td>
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<table>
<thead>
<tr>
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<tbody>
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</tr>
<tr>
<td>2</td>
<td>CONV – (N128, K7, S2), IN(N128), ReLU</td>
</tr>
<tr>
<td>3</td>
<td>CONV – (N256, K7, S2), IN(N256), ReLU</td>
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<tr>
<td>4</td>
<td>AdaptiveAvgPool1d(output_size = 1)</td>
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<tr>
<td>5</td>
<td>CONV – (N8, K1, S1)</td>
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<table>
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<tr>
<th>Layer</th>
<th>Decoder_MLP</th>
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<tbody>
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<td>FC(IN = 8, OUT = 256), ReLU</td>
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<tr>
<td>2</td>
<td>FC(IN = 256, OUT = 256), ReLU</td>
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<tr>
<td>3</td>
<td>FC(IN = 256, OUT = 3072)</td>
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<table>
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<tr>
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<th>Decoder_Up – sampling</th>
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<tbody>
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<tr>
<td>2</td>
<td>DCONV – (N64, K4, S2), AdaIN(N64), ReLU</td>
</tr>
<tr>
<td>3</td>
<td>DCONV – (N1, K7, S4)</td>
</tr>
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</table>

<table>
<thead>
<tr>
<th>Layer</th>
<th>Discriminator</th>
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<tbody>
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<td>DCONV – (N256, K4, S2), IN(N128), LeakyReLU</td>
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<td>4</td>
<td>DCONV – (N512, K4, S2), IN(N128), LeakyReLU</td>
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<td>DCONV – (N512, K3, S1)</td>
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<td>6</td>
<td>AvgPool1d(K1, S2)</td>
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