Stellar Populations of Galaxies in the LAMOST Spectral Survey

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Abstract

We first derive the stellar population properties: age and metallicity for ~43,000 low redshift galaxies in the DR7 of the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) survey, which have no spectroscopic observations in the Sloan Digital Sky Survey (SDSS). We employ a fitting procedure based on the small-scale features of galaxy spectra so as to avoid possible biases from the uncertain flux calibration of the LAMOST spectroscopy. We show that our algorithm can successfully recover the average age and metallicity of the stellar populations of galaxies down to signal-to-noise ratio ≥5 through testing on both mock galaxies and real galaxies comprising LAMOST and their SDSS counterparts. We provide a catalog of the age and metallicity for ~43,000 LAMOST galaxies online. As a demonstration of the scientific application of this catalog, we present the Holmberg effect on both age and metallicity of a sample of galaxies in galaxy pairs.

Unified Astronomy Thesaurus concepts: Galaxies (573); Stellar populations (1622); Spectroscopy (1558); Catalogs (205)

Supporting material: machine-readable table

1. Introduction

Galaxies are systems of stars, gas, and dust. A galaxy spectrum in an optical wavelength, which is mainly composed of the accumulated light of hundreds of billions of stars, encodes the age and metallicity distributions of stars. From stellar population analysis of galaxy spectra, the star formation and chemical evolution history of galaxies are expected to be decoded. The stellar population synthesis is the most widely used method to estimate the stellar population parameters by comparing the observed galaxy spectra to model spectra (Bica 1988; Vazdekis et al. 1996; Boisson et al. 2000; Bruzual & Charlot 2003; Cappellari & Emsellem 2004; Cid Fernandes et al. 2005; Ocvirk et al. 2006; Tojeiro et al. 2007; Maraston & Strömberg 2011; Chen et al. 2012; Wilkinson et al. 2017). There are many different synthesis algorithms using different characteristic spectroscopic information, e.g., the integrated spectral energy distribution (Cappellari & Emsellem 2004; Cid Fernandes et al. 2005; Ocvirk et al. 2006; Tojeiro et al. 2007; Cappellari 2017; Wilkinson et al. 2017) and specific absorption line features (Worthey et al. 1994; Kauffmann et al. 2003a, 2003b; Thomas et al. 2003; Vazdekis 2005; Thomas et al. 2011).

In recent years, a number of full spectral fitting algorithms have been publicly available, such as pPXF (Cappellari & Emsellem 2004; Cappellari 2017), STARLIGHT (Cid Fernandes et al. 2005), and FIREFLY (Wilkinson et al. 2015, 2017). These methods incorporate the full spectral information in the fitting process, and typically employ a chi-squared minimization approach to calculate the likelihood (or a posterior probability distribution) of galaxy physical properties by comparing observational spectra to a set of linear combinations of single stellar populations (SSPs). The outputs are a best-fitting combination of templates and a set of weights of these templates. Since the full spectral fitting methods use the information distributed along all the wavelengths of the spectrum, the fitting results are sensitive to the flux calibration of galaxy spectra. Though, the global shape of the continuum might be compensated by a multiplicative polynomial could compensate for the inaccuracy of the flux calibration has not been systematically tested. In practice, the order of the polynomial also can not be well-defined unless we have a detailed understanding of the uncertainties of the flux calibration.

Even if the flux calibration of spectra is good enough, there is still age–dust degeneracy in the full-spectrum fitting, especially for the galaxies with young stellar population (Pforr et al. 2012; Conroy 2013). To break this degeneracy, new algorithms have been proposed, in which the basic idea is to decompose the small-scale and large-scale signals in the wavelengths. For example, in the full-spectrum fitting code FIREFLY (Wilkinson et al. 2015, 2017), a high-pass filter is convolved with an observed spectrum so as to remove the long-wavelength mode of the spectrum and then do the spectral fitting. However, when the stellar populations of galaxies are complex, the filtered spectra can not be directly combined from the filtered SSPs (see Appendix A for a detailed discussion). Li et al. (2020) separates the small-scale features from the large-scale spectral shape by performing a moving average method and then fits the observed ratio of the small- to large-scale components (S/L) with the S/L ratios of the SSP models.
simultaneously. In this method, by fitting the S/L ratios, the
derived dust attenuation curves of galaxies could be equally
recovered without the knowledge of the continuum shape.
In this study, we aim to take the advantages of the fitting method
of Li et al. (2020) to estimate the stellar populations of galaxies
in the Large Sky Area Multi-Object Fiber Spectroscopic Telescope
(LAMOST) spectral survey, whose continuum shapes
of galaxy spectra are not very accurately calibrated.

The LAMOST is characterized by its capability of both a large
field of view and large aperture with an effective aperture of
3.6–4.9 m and 4000 fibers mounted on its focal plane (Cui et al.
2012; Zhao et al. 2012). The wavelength range of LAMOST
spectra covers 3700–9000 Å that is recorded in two arms, a blue
arm (3700–5900 Å) and a red arm (5700–9000 Å), with a
resolution of 1800 (Luo et al. 2015). When the blue and red
channels are combined together, each spectrum is rebinned in
spectra.

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of galaxy spectra are not very accurately calibrated.

2. Galaxies in LAMOST DR7

Our study is performed on the DR7 of the LAMOST spectral
survey, where 198,393 spectra of 166,691 objects have been
identified as galaxies. Among them, about 65% have spectral
counterparts in the 16th data release (DR16) of Sloan Digital
Sky Survey (SDSS; York et al. 2000; Ahumada et al. 2020).
In other words, about 66,648 spectra of 57,581 targets are only
observed spectroscopically by the LAMOST survey. There are
no spectroscopic observations of these targets in SDSS DR16.
The target selection of these galaxies in the LAMOST spectral
survey includes some specific science aims, for example, the
complementary galaxy sample (Shen et al. 2016; Feng et al.
2019), the LAMOST LCSSPA (Wu et al. 2016; Yang et al.
2019), and the red color shows the one for the new observations. The
gray color represents the distribution of all LAMOST galaxies, while the red color labels those of galaxies only
spectroscopically observed by the LAMOST spectral survey
but not by SDSS. The structure of this paper is as follows.
Section 2 describes the galaxy sample in the LAMOST spectra
survey. Section 3 presents the details of our spectral fitting
algorithm. In Section 4, we make tests on our fitting algorithm
using mock spectra and the repeated observations of LAMOST
and SDSS galaxies. In Section 5, we apply our method to the
galaxy spectra in the LAMOST spectral survey until DR7 and
present a catalog of their stellar population parameters.
Moreover, we present a scientific application of our catalog
by showing the Holmberg effects of galaxies in galaxy pairs.
The summary is given in Section 6. Throughout this study, we
adopt the cosmological parameters with $H_0 = 100\, \text{km} \, \text{s}^{-1} \, \text{Mpc}^{-1}$, $\Omega_M = 0.3$, and $\Omega_{\Lambda} = 0.7$.

Figure 1. Redshift and magnitude distributions of galaxies in the LAMOST
spectral survey DR7. The top panel is the redshift distribution, and the bottom
is the r band $\text{petroMag}_r$ distribution. The gray color represents the distribution
of all LAMOST galaxies, while the red color labels those of galaxies only
spectroscopically observed by the LAMOST.

![Figure 1](image-url)
only spectroscopically observed by LAMOST are 16.95 and 17.15, respectively, and the mean redshifts of these two samples are 0.998 and 0.103, respectively. As can be seen, both of them are comparable to those of the SDSS main sample galaxies (Stoughton et al. 2002).

In this paper, we focus on the spectra of galaxies that are only spectroscopically observed by the LAMOST survey and measure their stellar population parameters. In order to obtain reliable measurements, we restrict the LAMOST spectra with signal-to-noise ratio in r band (hereafter S/N\_r) ≥ 5. We get ~52,000 spectra (~43,600 targets) as our measurement data.

### 3. Fitting Method

In the typical stellar population synthesis, an observed galaxy spectrum is fitted with a combination of SSPs with different ages and metallicities. There are several widely used SSP models in the literature (Bruzual & Charlot 2003; Vazdekis et al. 2010; Maraston & Strömbäck 2011; Vazdekis et al. 2016; Conroy et al. 2018; Maraston et al. 2020). In this study, we use the SSP models from Vazdekis et al. (2010) hereafter V10 based on the empirical stellar library MILES (Sánchez-Blázquez et al. 2006), which has a wavelength range λ3540–7410 Å and a spectral resolution of 2.5 Å (FWHM) (Beifiori et al. 2011; Falcón-Barroso et al. 2011). V10 provides a sample of SSPs covering large stellar parameter regimes: age from 0.06 to 18 Gyr and metallicity from −1.71 to 0.22 (log (Z/Z⊙)).

We calculate the large-scale component of an observed spectrum by average filtering similar to Li et al. (2020). The window size for filtering is important to get the large-scale component. We have tested window sizes ranging from 100 to 700 Å, and finally choose 300 Å as the sliding window size. The testing process is described in details in the Appendix B. Note that before calculating the large-scale component, several well-known gas emission line regions such as Balmer series and some forbidden-line doublets have been masked.

After obtaining the large-scale component \(O_L(\lambda)\), we divide the observed spectrum by its large-scale component to get its small-scale component \(O_S(\lambda)\) by Equation (1). This definition of a small component can avoid being affected by uncertain flux calibration or dust attenuation.

\[
O_S(\lambda) = \frac{O(\lambda)}{O_L(\lambda)}
\]  

In the conventional full spectral fitting, the model spectrum \(M(\lambda)\) is a linear combination of the full spectra of SSPs. In order to fit the observed small-scale component, we also separate the small-scale component of \(M(\lambda)\) divided by its large-scale component \(M_L(\lambda)\). The small-scale feature of the model spectrum \(M_S(\lambda)\) is parameterized by,

\[
M_S(\lambda) = \frac{M(\lambda)}{M_L(\lambda)} = \frac{\sum_{i=1}^{N} a_i SSP_i(\lambda)}{\sum_{i=1}^{N} a_i SSP_i^l(\lambda)}
\]  

From Equation (2), we can see that the small-scale component of the model is a linear combination of the full spectra of SSPs divided by a linear combination of large-scale components of SSPs with the same weights \(a_i\).

After spectral decomposition of observed spectrum, we then make the classical minimum \(\chi^2\) fitting of the observed small-scale features with the small-scale component of the model:

\[
\chi^2 = \sum_\lambda \left[ O_S(\lambda) - \frac{\sum_{i=1}^{N} a_i SSP_i(\lambda)}{\sum_{i=1}^{N} a_i SSP_i^l(\lambda)} \right]^2
\]  

The fitting is performed by using a nonlinear least squares minimization routine LMFIT (Newville et al. 2014). In order to speed up the fitting process, we select 36 SSPs with 9 ages (0.06, 0.12, 0.25, 0.5, 1.0, 2.0, 4.0, 8.0, and 15 Gyr) and 4 metallicities (−1.71, −0.71, 0, and 0.22) from V10. The ages of SSPs are chosen with approximately equal intervals in logarithm space. For a better fit of the model, we linearly interpolate the SSPs to the same velocity scale of the observed spectra. During the fitting procedure, a set of fractional weights \(a_i\) with minimum \(\chi^2\) values is determined. And then the best-fitting model spectrum and mean age and metallicity can be obtained. Figure 2 illustrates an example of the whole fitting process using a mock spectrum.

(i) In Figure 2(a), we present a mock spectrum created from V10 SSPs with Gaussian S/N = 10. The spectrum is the full spectrum with large- and small-scale components. The construction of mock spectra is detailed in next section.

(ii) We apply the average filtering method to trace the large-scale component with a sliding 300-pixel window. The small-scale component is measured by dividing the input spectrum by its large-scale component. The large- and small-scale components are separately plotted in Figure 2(b).

(iii) In the fitting, the small-scale component of input spectrum is compared with the one of the model spectrum based on Equation (3) to determine the coefficients \(a_i\) of the best fitting. The fit result is shown in Figure 2(c), where the black spectrum is the small-scale component of the mock spectrum, and the red is the best-fitting small-scale component. We can see from the residuals of the input small-scale component to the best fitting that the fitting result of the small-scale components is good.

We reconstruct a full model spectrum by using a linear combination of SSPs with the coefficients \(a_i\) of the small-scale feature best fitting. The reconstructed model spectrum includes both large- and small-scale components, which are shown in red in panel (d). The black spectrum in panel (d) is the full spectrum of the mock. From residuals in the bottom panel of (d), we can see that the reconstructed full model spectrum is close to the input full spectrum, which indicates that coefficient \(a_i\) of the best-fitting small-scale component derived from our method can recover the input full spectrum to a good degree of accuracy.

(iv) Finally, using the coefficient \(a_i\), we estimate the average age and metallicity of the best-fitting solution using the following equations:

\[
\log(\text{Age}) = \frac{\sum_{i=1}^{N} a_i \log(t_i)}{\sum_{i=1}^{N} a_i}
\]  

and

\[
[M/H] = \frac{\sum_{i=1}^{N} a_i [M/H]_i}{\sum_{i=1}^{N} a_i},
\]  

where \(t_i\) and \([M/H]_i\) represent the age and metallicity of the \(i\)th SSP. Here, we provide light-weighted mean stellar population parameters. The comprehensive tests of our method are performed in next section.
our fitting algorithm by comparing the derived properties with the intrinsic values built in the mock spectra. The testing using the spectra of LAMOST and SDSS galaxies allows us to compare the stellar population properties derived from the LAMOST spectra using our method with their SDSS counterparts (which are believed to have a high accuracy of flux calibration) obtained from full spectral fitting.

4. Testing Our Fitting Method

To validate our fitting algorithm, we make tests using two sets of spectra: mock galaxies and real astronomical galaxies from LAMOST and SDSS observations. The testing using mock galaxies based on SSPs is to explore a possible bias in the stellar age and the red is the best-fitting solution. In panel (d), the red spectrum is a model spectrum reconstructed from a linear combination of SSPs with the coefficients of our small-scale feature best fitting, and the black is the full spectrum of the mock. In the bottom of panels (c) and (d), we show the residuals of the black spectrum to the red one.

4.1. Testing with Mock Galaxies

We create mock galaxies using the SSP templates from V10 (Vazdekis et al. 2010). We choose SSPs covering 25 ages from 0.06 Gyr to 15 Gyr and four metallicities from $-1.71$ to 0.22 ($\log (Z/Z_{\odot})$) to generate the mock spectra. For each metallicity, we randomly pick one from the 25 SSPs with different ages, which results in four selected SSPs with different metallicities and ages. Then, a combination of the four SSPs with random weights can generate one mock spectrum. The intrinsic mean age and metallicity of this mock spectrum are computed by combining ages and metallicities of the four SSPs with their corresponding weights. We repeat the above step 1000 times and then build 1000 synthetic mock spectra. In addition, we create about 200 high metallicity ($-0.25, 0.22$) spectra to supplement the high metallicity end of the mock sample. In order to better simulate the real spectra, we redder the spectra in the mock sample by using the Calzetti dust extinction curve (Calzetti et al. 2000) assuming color excesses $E(B-V)$ randomly selected from a range (0.01 to 0.2).

And then, we apply a Gaussian perturbation to each flux pixel of these mock spectra with $S/N = 5, 10, 20,$ and 30, as described by the following equation:

$$F_{\text{mock}}(\lambda_i) = F_{\text{mock}}(\lambda_i) + N(0, \frac{F_{\text{mock}}(\lambda_i)}{S/N})^2 \right)^2, \quad (6)$$

where $F_{\text{mock}}(\lambda_i)$ is the flux of the mock galaxy at wavelength $\lambda_i$, $F_{\text{mock}}(\lambda_i)$ is its corresponding flux free of noise, and $N(\mu, \sigma^2)$ is a Gaussian perturbation with $\sigma^2$ characterized by the given $S/N$.

Finally, we obtain a total of 4800 mock spectra as our testing sample. For each $S/N$, there are 1200 mock spectra in our testing sample.

We run the fitting process detailed in Section 3, and measure the mean age and metallicity of each mock spectrum. We then compare the fitting results with the intrinsic values of the mock spectra, which are illustrated in Figures 3 and 4. Figure 3 shows the comparison of the fitted mean ages and metallicities with intrinsic values for the mock spectra with $S/N = 10$, where good linear correlations are clearly seen. The mean ($\mu$) and standard deviation ($\sigma$) of differences between our fitting results and the intrinsic values are also indicated in each panel. For age, the standard deviation is $\sim 0.15$. For metallicity, the standard deviation is slightly larger with the value $\sim 0.19$. In Figure 4, we describe the variation of the differences between our derived parameters and the intrinsic values along with $S/N$. As expected, the deviation decreases when $S/N$ increases. For stellar age, the consistence is within 0.2 dex even down to $S/N = 5$. The deviation of the stellar metallicity measurement is large, which may be caused by the lesser number of metallicity grids used in fitting or the complexity of the metallicity measurement from the galaxy spectrum (Girardi et al. 2000; Bruzual & Charlot 2003; Gallazzi et al. 2005).
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As we can see from the testing results of the mock galaxy spectra that our method based on the small-scale component works well even if we consider the dust attenuation effect into the mock spectra. In fact, the dust attenuation effect of spectrum being the large-scale component is filtered out during our fitting process.

4.2. Testing with SDSS Galaxies

In this section, we further test our fitting code using the spectra of real galaxies. We make comparisons of the fitting results on the galaxy spectra with both observations in the SDSS and LAMOST spectra survey. Specifically, we derive the stellar population parameters from the LAMOST spectra using the method outlined above, and compare with results from the SDSS spectra using the classical full spectral fitting.

We first get the same target observations from LAMOST and SDSS by cross-matching the galaxy spectra in LAMOST DR7 with the counterparts in SDSS DR16 with $S/N_0 \geq 5$. In order to eliminate the difference of $S/N$ between the LAMOST and SDSS spectra, we restrict the counterparts in the two samples with $|S/N_{\text{LAMOST}} - S/N_{\text{SDSS}}| < 1$. We then obtain $\sim 7000$ spectra of LAMOST and their SDSS counterparts as our testing samples. For the LAMOST spectra, we use our method to derive the stellar population parameters based on the small-scale features, while for SDSS spectra, we use pPXF (Cappellari & Emsellem 2004; Cappellari 2017) to make the full spectral fitting. The templates we used in pPXF are the same 36 MILES SSPs as our method described in Section 3. During the pPXF fitting, we adopt a high-order multiplicative polynomial to mimic the spectra reddening effect and without adopting a specific reddening curve. In addition, we do not apply a regularization to the star formation history in the pPXF fitting, because we focus on the weighted mean age and metallicity of the galaxy rather than the smooth history in the pPXF fitting. This is precisely the reason for the need to develop the small-scale feature fitting method for the LAMOST spectra in this paper.

In addition, we consider the effect of $S/N_r$ on the difference of the stellar population parameters between our method on the LAMOST spectra and the pPXF full spectrum fitting on the SDSS spectra. Figure 6 displays the dispersion of the differences as a function of $S/N_r$. We see that, as the $S/N_r$ increases, the dispersion of the differences decreases significantly. From these comparisons, we see that our small-scale feature fitting method can obtain a reliable estimation (with an accuracy better than 0.25 and 0.3 dex for age and metallicity, respectively) on the average stellar populations of galaxies for the LAMOST spectra with $S/N$ down to 5.

In conclusion, as illustrated by the above tests, our small-scale feature fitting method is fully adapted to the estimation of the stellar population parameters for the LAMOST galaxy spectra. The main benefit of our method is to avoid possible biases from the uncertain flux calibration of the LAMOST spectroscopy.

Figure 3. Comparisons of the ages and metallicities between our derived parameters and intrinsic values of the mock spectra with $S/N = 10$. The top panel shows the comparison of ages in log (yr), and the bottom displays the comparison of metallicities in log ($Z/Z_\odot$). The mean and standard deviations of the differences are given in the top left corner of each panel. Note that the points out of $3\sigma$ are clipped in each panel. The red line is the identity line ($y = x$).

Figure 4. Differences between the stellar population of mock spectra derived by our method and their intrinsic values as a function of $S/N$. The error bars express the median values and the standard deviations of the differences in each $S/N$ bin. There are clear declines with $S/N$ increasing.

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5. Application to LAMOST Galaxy Spectra

We apply our small-scale feature fitting algorithm to the LAMOST galaxy spectra that have not been spectroscopically targeted by SDSS to derive their stellar population parameters. After fitting, with an extensive visual inspection, we exclude a few spectra (less than 1.5%) that are badly fitted. Finally, we have obtained the stellar population parameters of $\sim 43,000$ galaxies. (If a galaxy has more than one spectrum, we keep the spectrum with the highest $S/N_r$.)

5.1. The Catalogue of Stellar Population Properties for LAMOST Galaxies

We present the catalog of our derived stellar population properties (age and metallicity) as a value-added catalog for $\sim 43,000$ galaxies in LAMOST DR7. All the galaxies in our catalog are only spectroscopically observed by LAMOST but without spectral counterparts in SDSS DR16. Table 1 lists a part of this catalog. The complete catalog is available online.

Figure 5. Comparisons of the age and metallicity measurements for the galaxies with both LAMOST and SDSS spectra ($S/N_r \geq 10$). The left two panels show the comparisons between the LAMOST spectra fit with our small-scale feature method and their SDSS counterparts fit with the full spectral fitting. The right two panels compare the results from the same full spectrum fitting method for the LAMOST and SDSS spectra. Note that the points out of $3\sigma$ are clipped in each panel. The red line is the identity line ($y = x$).

Figure 6. Dispersion of the differences of the stellar population parameters between the LAMOST spectra measured by our method and their SDSS spectral counterparts using the full spectral fitting as a function of $S/N_r$. The top panel shows the dispersion of $\Delta \log \text{Age}$, and the bottom panel plots that of $\Delta [M/H]$. The error bar expresses the median value and the standard deviation of the differences in each $S/N_r$ bin. There are clear declines with $S/N_r$ increasing.
Figure 7 shows the distribution of age and metallicity in our catalog for different bins of stellar mass. The stellar masses of our galaxies are estimated using magnitudes in $r$ band and stellar mass-to-light (M/L) ratios. The M/L is derived from a function of $g - r$ color given by Bell et al. (2003). We see from Figure 7 that the age and metallicity of galaxies increase as stellar mass increases.

5.2. A Scientific Application of the Stellar Population Properties of LAMOST Spectra

An interesting science target selection in the LAMOST spectral survey is the complementary galaxy sample that is a subset of the MGS of SDSS without spectroscopic observations until DR7. We recall that the MGS of SDSS is a magnitude-complete galaxy sample down to $<17.77$ (Stoughton et al. 2002). As shown by Shen et al. (2016), those MGS in SDSS without spectroscopic observations are mainly caused by the fiber collision effect, so these galaxies targeted in LAMOST are probably in the galaxy pair environment. As a result, some galaxies in our catalog are indeed members of galaxy pairs.

Here we present an application of the stellar population measurements of the galaxies in our catalog, the Holmberg effect on the galaxies in pairs, which tells that the physical properties of the pair members are correlated (e.g., color; Holmberg 1958; Tomov 1978; Allam et al. 2004; Cao et al. 2016). However, whether this correlation is caused by a nature or nurture effect is still not clear (Allam et al. 2004; Deng et al. 2010; Melnyk et al. 2012).

Following Feng et al. (2019), we select the galaxy pairs using two criteria about the line-of-sight velocity difference ($\Delta V$) and the projected distance ($r_p$): $\Delta V \leq 500 \text{ km s}^{-1}$ and $10 \ h_{70}^{-1} \text{ kpc} \leq r_p \leq 200 \ h_{100}^{-1} \text{ kpc}$. By matching galaxies in our catalog with ones in SDSS MGS by the above criteria, we obtain a sample of $\sim 3000$ LAMOST-SDSS galaxy pairs. To better outline the Holmberg effect, we construct a control sample to our $\sim 3000$ LAMOST members in the pair sample by a process similar to Ellison et al. (2008). To be specific, a control sample is compiled by matching each pair galaxy in the same mass and redshift distributions with the galaxies with no close companions in SDSS MGS. We confirmed that the galaxies in the control sample are physically uncorrelated ($r_p > 200 h_{100}^{-1} \text{ kpc}$), and also have nearly identical distributions of redshift and stellar mass to the pair sample.

The differences of the ages and metallicities of two members of the pair and control sample are shown in Figure 8. In each panel, the red histograms represent the differences of members in the pair sample, while the blue histograms show the differences in the control sample. The standard deviation ($\sigma$) of $\Delta \log \text{Age}$ and $\Delta [M/H]$ are indicated in red and blue with the same color meaning as the histograms. From the figure, we see that the distributions of differences of the age and metallicity of the paired galaxies have significantly smaller scatter than the control galaxies. Since the pairs and their controls have the same mass and redshift, the correlation between the magnitudes (in that, colors) of the pair members has been reflected in the control sample. If we consider the correlation between the masses of pair members as a nature effect (Feng et al. 2019), in the smaller scatter of $\Delta \log \text{Age}$ and $\Delta [M/H]$, we see for the pair members should originate from coevolution of pair members, i.e., the nurture effect.
give a preliminary study on the Holmberg effect of galaxy pairs in our catalog, which may play an important role in the study of the physical properties of the low redshift galaxies and galaxy systems. In the next work, we plan to apply our small-scale feature fitting to all LAMOST galaxies, and continuously update the stellar population catalog as a value-added catalog available on the LAMOST official website.

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Appendix A

Modeling the Galaxy Spectrum Based on Small-scale Component

In the conventional full spectral fitting, the spectrum of a galaxy $S(\lambda)$ could be modeled by a linear combination of SSPs,

$$S(\lambda) = \frac{1}{\Delta \lambda} \int_{\lambda - \Delta \lambda/2}^{\lambda + \Delta \lambda/2} S(\lambda') d\lambda',$$

where $a_i$ is the fraction of the stellar population SSP$_i$, and $D(\lambda')$ represents modification of the spectrum by either the uncertainties of flux calibration or the dust attenuation effect.

Following Li et al. (2020), we define the large-scale component of a galaxy spectrum as,

$$S_L(\lambda) = \frac{1}{\Delta \lambda} \int_{\lambda - \Delta \lambda/2}^{\lambda + \Delta \lambda/2} S(\lambda') d\lambda',$$

where $\Delta \lambda$ is the wavelength window size. Using Equation (A1) in the above equation, we get

$$S_L(\lambda) = \frac{1}{\Delta \lambda} \int_{\lambda - \Delta \lambda/2}^{\lambda + \Delta \lambda/2} \left[ \sum_{i=1}^{N} a_i SSP^i(\lambda') \right] d\lambda' \approx \frac{D(\lambda)}{\Delta \lambda} \int_{\lambda - \Delta \lambda/2}^{\lambda + \Delta \lambda/2} \left[ \sum_{i=1}^{N} a_i SSP^i(\lambda') \right] d\lambda' = \left[ \sum_{i=1}^{N} a_i SSP^i_L(\lambda) \right] \cdot D(\lambda),$$

where SSP$_L^i$ is the large-scale component of SSP$_i$ following the same smooth process of Equation (A2). The approximation in this equation is based on the fact that $D(\lambda)$ is a large-scale correction factor and could be approximated as a constant inside the window function $\Delta \lambda$. Then, the small-scale

6. Summary

In this study, we explore a fitting method based on the small-scale features of galaxy spectra to derive the basic stellar population parameters, the mean stellar age, and the metallicity, for the LAMOST galaxy spectra. The core of our method is to separate the small-scale features from the large-scale components and only fit the small-scale features of the observed spectra to the small-scale features of models using Equation (3). Generally, the large-scale component is regarded as the continuum shape, while the small-scale component represents the spectral lines. So our method mainly relies on absorption line features in galaxy spectra independently of the continuum shape. One important advantage of this method is that it is suitable for the stellar population analysis of galaxies with uncertain flux calibration or spatially nonuniform dust attenuation. We check the performances of our method using mock galaxies and real observed spectra of LAMOST and SDSS galaxies, and the results show a good consistency within 0.2 dex despite higher uncertainties (0.25 dex and 0.3 dex for age and metallicity, respectively) for galaxies in $S/N = 5$.

Another goal of this paper is to present a public catalog of stellar age and metallicity for galaxies only spectroscopically observed in LAMOST DR7, but without spectral counterparts in SDSS DR16, using our fitting method. As a result, a catalog of stellar population parameters for $\sim$43,000 galaxies is published, which is the first estimation of the age and metallicity for galaxies in the LAMOST spectral survey. We

Figure 8. Distributions of the differences of age and metallicity of two members in the pair sample and control sample. In each panel, the red histograms express the differences of two companions in the pair sample, and the blue histograms describe the differences of the control galaxies. The standard deviations ($\sigma$) of $\Delta$[log Age] and $\Delta$[M/H] of the two samples are labeled in the top left of each panel with the same color coding as the histograms.
component of the galaxy spectrum is simply written as

$$S_5(\lambda) = \frac{S(\lambda)}{S_5(\lambda)} = \frac{\sum_{i=1}^{N} a_i \text{SSP}_i(\lambda)}{\sum_{i=1}^{N} a_i \text{SSP}_i(\lambda)}.$$  \hspace{1cm} (A4)

If the stellar populations of the galaxy we study can be well approximated by one SSP, we have

$$S_5(\lambda) = \frac{\text{SSP}_i(\lambda)}{\text{SSP}_i(\lambda)} = \text{SSP}_i^i(\lambda),$$  \hspace{1cm} (A5)

where SSP$^i$ is defined as the small-scale component of SSP accordingly. That is to say, in this case ($N = 1$), we can model the small-scale component of the galaxy with SSP$^i$ directly and thus eliminate the unknown factor $D(\lambda)$. On the other hand, when the stellar populations of the galaxy are complex ($N > 1$), we cannot fit $S_5(\lambda)$ with a linear combination of SSP$^i$, because

$$S_5(\lambda) = \frac{\sum_{i=1}^{N} a_i \text{SSP}_i(\lambda)}{\sum_{i=1}^{N} a_i \text{SSP}_i(\lambda)} = \sum_{i=1}^{N} a_i \text{SSP}_i.$$  \hspace{1cm} (A6)

## Appendix B

### The Choice of Window Size for Calculating the Large-scale Component

We use average filtering to calculate the large-scale component of the spectrum. The sliding window size is an important factor in the calculation. In order to find a suitable window size, we test different window sizes ranging from 100 to 700 Å in our fitting method using the mock galaxies created in Section 4.1, and compare the standard deviation $\sigma$ of the difference between our derived stellar populations and intrinsic values. Figure 9 plots $\sigma$ as a function of the window sizes for four different S/Ns (5, 10, 20, and 30). We see that the changes of $\sigma$ do not have effects on our fitting results when the window size is >200 Å. Generally, when the window size is larger, the computational time is larger. In order to balance the window size and computational time, we finally choose 300 Å as the window size for calculating the large-scale component.

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