Preserving Structure in Multi-wavelength Images of Extended Objects

James Pizagno

ABSTRACT

A non-parametric smoothing method is presented that reduces noise in multi-wavelength imaging data sets. Using Principle Component Analysis (hereafter PCA) to associate pixels according to their ugriz-band colors, smoothing is done over pixels with a similar location in PCA space. This method smooths over pixels with similar color, which reduces the amount of mixing of different colors within the smoothing region. The method is tested using a mock galaxy with signal-to-noise levels and color characteristics of SDSS data. When comparing this method to smoothing methods using a fixed radial profile or an adaptive radial profile, the $\chi^2$-like statistic for the method presented here is smaller. The method shows a small dependence on input parameters. Running this method on SDSS data and fitting theoretical stellar population models to the smoothed data of the mock galaxy and SDSS data, shows that the method reduces scatter in the best-fit stellar population analysis parameters, when compared to cases where no smoothing is done. For an area centered on the star forming region of the mock galaxy, the median and standard deviation of the PCA-smoothed data is 7 Myr ($\pm$ 3 Myr), as compared to 10 Myr ($\pm$ 1 Myr) for a simple radial average, where the noise-free true value is 7.5 Myr ($\pm$ 3.7 Myr).

Subject headings: galaxies: stellar populations, data: analysis algorithms

1. Introduction

Galaxy formation theories predict that baryons cool in dark matter halos in such a way as to provide connections between galaxy observables and dark matter properties (White & Rees 1978; Cole & Kaiser 1989). For example, the Tully-Fisher relation (Tully & Fisher 1977) shows the connection between galaxy luminosity and circular velocity, where the circular velocity depends on the dark matter and baryonic mass profiles. A key tool in studying galaxy evolution is the semi-analytic model approach to relating the observable properties of galaxies to the underlying formation physics (Eisenstein & Loeb 1996; Mo et al. 1998). Semi-analytic models of galaxy formation predict observables such as the luminosity function, radii, rotation curves, clustering statistics, colors, and the stellar mass of galaxies. Gnedin et al. (2007) and Dutton et al. (2007) have shown that semi-analytic models can predict the joint distribution of galaxy observables, with model parameters

1jpizagno@u.washington.edu, Department of Astronomy, University of Washington, Seattle, USA
that depend on the baryonic mass profile, where the baryonic mass profile includes the stellar mass and gas mass. Budgeting baryonic mass into stellar mass and gas mass is an important tunable parameter in the modeling (McGaugh 2005). One major difficulty lies in converting multi-wavelength imaging data into the stellar mass, where the multi-wavelength imaging data is inherently noisy.

Large surveys produce multi-wavelength maps of galaxies, which are used to measure the baryonic properties of the galaxy population. Large surveys produce large data sets, which are comparable in size to modern simulations (De Lucia et al. 2006; Bower et al. 2006). Since models of galaxy formation predict stellar mass and surface density, the multi-wavelength maps of galaxies must be converted into stellar populations using synthetic stellar population models (Maraston 2005; Bruzual & Charlot 2003). In order to analyze the stellar populations in multi-wavelength images of galaxies, noise-reduction techniques must be employed. Large surveys are key to answering these questions because they provide data uniformity over a large area of the sky. SDSS provides ugriz-band data over 25% of the sky with a photometric calibration accuracy good to 2% (Ivezic et al. 2004). The existence of these noisy, but uniform and large, data sets, along with the need for stellar population modeling, requires a smoothing technique for multi-wavelength data sets.

A study similar to this one is (Lanyon-Foster et al. (2007); hereafter L07), which studies the pixel color magnitude relation for nearby galaxies. L07 noted the distinct difference of pixel color magnitude diagrams with different Hubble types, where Early-type galaxies have redder pCDMs. L07 noted how morphological features were related to distinct features in the pCDM. Scatter in a pCDM was caused by extinction, showing the need for accurate ISM extinction models when modeling observed colors. The study by L07 shows how pixel maps of galaxies are correlated with galaxy type, and might reveal hidden features. L07 does not employ noise-reduction techniques, such as the ones presented in this paper, which may affect the structure of the pixel diagrams.

Another study similar to this one is Welikala et al. (2008). Welikala et al. (2008) used the pixel-z technique, which combines stellar population synthesis models with multi-wavelength pixel photometry of galaxies to study the stellar population content of SDSS galaxies. Welikala et al. (2008) showed how the star formation rate varies with local galaxy density, varies with position in a galaxy, and studied the mean star formation rate. The pixel-z method does not include any smoothing techniques. This current work will be complementary to that work, by providing a smoothing technique that will minimize the effect data noise will have on the best-fit stellar population parameters.

Adaptsmooth (Zibetti, Charlot, Rix 2009) is a multi-wavelength smoothing algorithm that is similar to this work. Adaptsmooth uses a circularly symmetric radial median to reduce noise. The radius of the circle is defined so that median smoothed data has a signal-to-noise of 20. All of the imaging wavelength data (i.e. ugriz-bands) are smoothed to the same radius, which is determined from the maximum radius of the multi-wavelength data in question, which is usually the u-band or z-band in SDSS data as they have the lowest signal-to-noise. Adaptsmooth is adaptive, in the
sense that the radius varies with position in the galaxy, as the signal-to-noise varies. However, the radial median filter is still azimuthally symmetric. This means that blue star formation regions can get median filtered together with redder disk. The PCA-smoothing method presented in this paper, median filters over pixels that are associated in PCA space according to their color.

We focus on SDSS because it is a large and uniform data-set. SDSS has coverage over 25% of the sky, where the imaging data covers a large range of optical wavelengths, and does so in a uniform manner. The distribution of galaxy properties has been well studied for SDSS data sets (Blanton et al. 2003). Many semi-analytic models have been constrained using SDSS data (Gnedin et al. 2007; Li et al. 2007).

In the following paper the technique is described in Section 2, a comparison to other methods is done in Section 3, case studies are presented in Section 4, and the conclusion is presented in Section 5.

2. Technique

The goal of this method is to smooth data without mixing different colors. For example, a simple radial smoothing method may mix a red bulge with a blue star forming region, which will result in poorly fit stellar population models. The method must be automated so that it can be applied to large data sets, such as the SDSS, and not have input parameters that vary within the data-set. Since the noise characteristics may vary among different data sets (i.e. SDSS vs. 2MASS), the method must also have tunable parameters. It is shown below that an advantage of this method is that it is not overly sensitive to the input parameters.

The method presented here uses Principal Component Analysis (hereafter PCA) in order to quantitatively associate pixels according to their color. PCA can be used to reduce the dimensionality of data, illuminate hidden correlations, quantify levels of proportionality, and rotate data into new axes. PCA has been used in many different areas of data analysis, and has been described in detail in other papers using it as an analysis tool for astronomical spectra (Yip, et al. 2004; Connolly et al. 1993). PCA is used here as a way to associate pixels according to their color and spatial location. This method transforms the multi-wavelength data, from color as a function of position in the galaxy to eigenweights of basis colors as a function of position in PCA space. Poisson noise is reduced by averaging over pixels having similar PCA weights, or similar locations in PCA space.

2.1. Mock Galaxy

For several reasons, the method presented here is tested using a mock galaxy. First, the mock galaxy can be assigned a wide range of colors, representing those seen in real data sets. The
colors used here resemble the colors of recent star formation for the HII-like regions, old stellar populations for the Bulge, intermediate populations for the Disk, and dust is applied to different spatial regions. Secondly, the effects of noise on different colors can be estimated by adding Poisson noise due to the source and background. Thirdly, the mock galaxy is assigned spatially variable colors with realistic spatial structures which may cause over simplified smoothing methods to fail. For example, real galaxies tend to have a high signal-to-noise bulge with old reddish color, whereas the disk contains a fainter intermediate age color with a moderate-to-low signal-to-noise value, and there are asymmetric HII regions with a young stellar populations that have high signal-to-noise values. Real galaxies have blue high SNR HII regions that are only a few FWHMs from a faint red dust lane. Over simplified mapping techniques may average these colors together. Fourthly, using a mock galaxy provides the “truth”. Knowing the true noise-free colors will allow a figure of merit to be calculated which can be used to test different techniques discussed in this paper.

The goal is to create a mock galaxy with realistic spatial variations of the underlying color and SNR values that are similar to SDSS data. The components of the mock galaxy are a bulge, disk, spiral arms, star formation regions, and dust. Using GALFIT (Peng et al. 2002), 5 different images are created, which represent the ugriz-band respectively. Each component has the color of a specific stellar population model. Star formation is spatially modeled as an arc of point sources along the spiral arms. A PSF, as a function of wavelength, was measured from real SDSS data, and was added to the GALFIT input file. The wavelength dependent extinction is applied to the ugriz-band mock images using the extinction curve in (Cardelli, Clayton, Mathis 1989) and assuming a selective extinction value of $R_V = 3.1$. The PSF is then measured using stars at edge of the image, which were added by GALFIT as point-sources and the user-provided PSF. A mock galaxy was made that includes spatially varying colors, with dusty regions that are generated from low-pass filtering of a real galaxy.

Typical SDSS sky values for each band are added to the ugriz images of the mock galaxy. This is required to reproduce the SNR seen in SDSS data. Poisson noise, including source and sky, is added to the images of the mock galaxy. The resulting $g$-band and $r$-band images are shown in Figure 1. Figure 1 shows the bulge, spiral arms, star formation regions, and dust regions. These features qualitatively represent real SDSS data, in the sense that the color varies with position and the features are asymmetric. The mock galaxy matches the observed properties of SDSS galaxies with blue star formation regions and a red bulge, with a color of $g - r = 1.2$ for the bulge, $g - r = 0.37$ for the exponential disk, $g - r = -0.63$ for the star formation regions, and the patches of dust produce regions that are typically $\Delta(g - r) \sim 0.12$ redder than the surrounding dust-free regions. Adding sky and source noise results in total signal-to-noise values that vary from 50.0 in the center of the bulge to 5-7 at the disk half-light radius, to nearly 0 where the outer parts of the disk fade into the sky background. For example, the bulge of the mock galaxy has an $r$-band flux $= 1500$ DN on average, where the typical HII $r$-band flux $= 150-180$, which is comparable to the galaxies from SDSS in Section 4.

In the analysis steps below, the mock data is treated as if it were real SDSS data. PSFs
are measured from point sources in the image. The PSF of each image is matched to the $u$-band PSF, because it is the broadest PSF. The background sky was measured from the corner of the images and subtracted from the data. Before this method can be applied, the data must have PSFs matched, all instrument artifacts removed, and the galaxy identified.

### 2.2. PCA Application

The method proposed here uses the results of PCA to determine a quantitative relationship between the colors of different pixels, which are associated during the smoothing process. It is assumed that each pixel is a linear combination of basis spectra. The flux at any pixel can be described as a linear combination of a set of weighted basis spectra. The normalized flux at pixel $(x,y)$ can then be written as:

$$ F_{\lambda}(x,y) = \sum_{i=1}^{5} a_i(x,y)e_{\lambda,i} \tag{1} $$

where $i$ is the number of bands (5 for SDSS), $x$ and $y$ are spatial position in this galaxy, and $\lambda$ denotes the band (i.e. $ugriz$), $a_i(x,y)$ is a eigenweight which varies as a function of position in the galaxy, and $e_{\lambda,i}$ is the $i$th basis at band $\lambda$.

The covariance matrix method is used to measure the eigenvectors and eigenvalues. The data are first normalized to the $r$-band. All pixels within 2 disk scale lengths and having a SNR ratio greater than a minimum value (discussed later) are included in a data matrix. Using lower signal-to-noise values lower than this includes pixels heavily influenced by background sky colors. The covariance matrix of this data matrix is calculated, and then the eigenvectors and eigenvalues of this covariance matrix are determined. This is carried out using Python procedures in the NUMPY.LINALG library, where the eigenvectors are solved using the APACK routines dgeev and zgeev.

Figure 2 shows the location of pixels within a subsection of the mock galaxy image. The figure color-coding is made according to spatial location in the galaxy. Pixels in similar areas of the left-hand panel of Figure 2 have similar colors. This method divides the PCA-space into evenly spaced angular bins. Angular bins are chosen, as opposed to a linear interpolation, to follow the observed trend seen in PCA-space. A small variation in color can result in a large variation in best-fit stellar population parameters. For example, a $(g-r)$ color change of 0.3 can cause an estimate of the mass-to-light ratio to change by a factor of 3 (Figure 6 of Bell et al. (2003)). Therefore, the number of bins is chosen to have a standard deviation in $g-r$ color that will minimize the scatter in best-fit parameters. The number of bins used in smoothing is a free parameter, which can be adjusted by the user. The implementation here uses 10 bins because using too few bins will produce averaging over different colors, whereas using too many bins will have bins that are so narrow that almost no

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1http://www.netlib.org/lapack/
Averaging is done over pixels that are in similar areas of both PCA-space and spatial regions of the galaxy. For example, using 5 bins breaks the PCA-space up so broadly that pixels in the same bin have a broad distribution with a standard deviation of $\delta(g-r) = 0.8$, whereas using 10 bins has a standard deviation of typically $\delta(g-r) = 0.3$. To enhance the SNR, smoothing is done over pixels within a range of angular bins, where the range of bins is inversely proportional to that pixel’s total signal-to-noise ratio. More specifically, for a pixel with total signal-to-noise $SNR(x,y)$, all pixels within the integer-value of $SNRenhanced/SNR(x,y)$ angular bins are median filtered together. For example, using an input parameter of $SNRenhanced = 70$ for a pixel with a $SNR(x,y) = 30.0$, median filters within $\pm 2 (= \text{int}(70/30))$ bins in the left-hand panel of Figure 2. The parameter $SNRenhanced$ is a constant for a given data set, and will be determined using the mock galaxy for the SDSS data set described here. This formulation has two effects. First, pixels with lower signal-to-noise values are averaged over more pixels. Secondly, the averaging is over pixels with similar colors in PCA space (Figure 2).

A figure of merit metric ($FOM$) is used to quantitatively determine the best smoothing technique. It should be the difference between the truth and smoothed data, consider all wavelengths, and be inversely proportional to the total noise value. The $FOM$ is defined as:

$$FOM(P, N) = \sum_{x,y}^N \sum_{\lambda=1}^5 \frac{(Truth_{\lambda}(x,y) - Smooth_{\lambda}(x,y|P))^2}{(\sigma_\lambda(x,y))^2}, \quad (2)$$

where $Truth_{\lambda}(x,y)$ is the true flux at band $\lambda$ at spatial position $(x,y)$, $Smooth_{\lambda}(x,y|P)$ is the smoothed flux at band $\lambda$ at spatial position $(x,y)$, $P$ is the list of free parameters ($SNR_{max}$, $SNR_{min}$, $Radius$, $SNRenhanced$), $\sigma_\lambda$ is the noise in band $\lambda$, and $N$ is the number of pixels. $SNR_{max}$ is the maximum SNR ratio of the pixels to which the method is applied. $SNR_{min}$ is the minimum SNR over which smoothing is applied. $Radius$ gives the size of the circle for pixels that may be included in the mean. $SNRenhanced$ is a constant controlling the range of pixels in PCA space that are included in the smoothing. The free parameters are then the ones mentioned above in $P$, along with the region within which the PCA eigen-vectors are measured, and the number of PCA bins. The best-fit parameters for the SDSS data-set are determined using a grid-search method, which searches for the parameters $P$ which provide the minimum $FOM$. The $FOM$ is defined in such a way that a lower $FOM$ is a better estimate of the true colors.

Figure 3 shows the region over which this experiment is run. The range of parameters searched was $6 < SNR_{max} < 200$, $0 < Radius < \text{size-of-image}$, $6 < SNRenhanced < 600$, and $0 < SNR_{min} < 9$, and results are shown below for most of that range. The bottom panels of Figure 3 show the PCA map and smoothed PCA image. The bottom left panel shows the combination of location of each pixel in the angular bin seen in Figure 2 and which pixels are included in smoothing. The HII-like regions and bulge are clearly in different locations in PCA space, as can be seen by the fact that they have different gray scales (angular bins). The bottom right panel shows the image smoothed by pixels associated in PCA space (PCA-smoothing). The contrast in the smoothed image resembles the noise-free image (top left panel).
2.3. Analysis

Figure 4 shows the FOM versus the free-parameters for the region in Figure 3. The lines show how the FOM varies with the variable on the x-axis as the parameters in the key are held fixed. The left panel of Figure 4 shows how the FOM varies as the maximum SNR value is varied. The FOM has a minimum between 30 < SNRmax < 50. The reason the FOM doesn’t get smaller as SNRmax increases is because there are so few pixels with such high SNR values. The middle panel of Figure 4 shows how the FOM varies with the smoothing radius. For radii smaller than 3 the FOM increases because less smoothing is done. For radii larger than 4, the FOM does not increase because only pixels with similar positions in PCA-space of Figure 2 are included in the median. The right panel of Figure 4 shows the FOM as the SNRenhanced constant is changed. This figure shows that any SNRenhanced value greater than 40 will give an acceptable fit. Increasing the SNRenhanced value increases the number of bins over which pixels in PCA-space are smoothed. The FOM does not increase as SNRenhanced is increased because only pixels within a fixed spatial area (circle of radius 2-5) are included in the fit, and this mock galaxy does not have HII-like regions within a few pixels of the bright red bulge. The FOM does not change drastically as the parameters are changed slightly, demonstrating the robustness of PCA smoothing.

Figure 5 shows the FOM versus the method parameters for a region centered on the HII-like star forming arc. The left panel of Figure 5 shows how the FOM varies with SNRmax. The FOM has a minimum between 20 < SMRmax < 50. The middle panel of Figure 5 shows how the FOM varies with Radius. The FOM has a minimum between 2 < Radius < 4. The right panel of Figure 5 shows how the FOM varies with the SNRenhanced. The SNR decreases rapidly to about SNRenhanced = 60, and then does not decrease drastically. It does not increase for this data because the HII-like region is not close to the red color bulge. The variation of SNRmin is not shown, because as long as it is SNRmin = 3, there is an acceptable fit. These parameters, being only slightly different from the globally determined best-fit parameters, show the robustness of this method. Considering Figures 5 and Figure 4 the best-fit parameters are SNRmax=30.0, Radius=4.0, SNRenhanced=60.0 and SNRmin=3.0.

Figure 6 shows a map of pixels included in the smoothing for a single pixel in the mock galaxy image. The pixels with green crosses are included in the median average when smoothing for the central pixel. The circle is the best-fit radial aperture of Radius = 4 pixels. The pixels with green crosses all have similar locations in PCA-space (left panel of Figure 2) and SNR range (right panel of Figure 2). This figure shows that most of the pixels included in the median filter are HII-like region pixels.

Figure 7 shows the change in total SNR for pixels centered on the HII region. The SNR per pixel after PCA smoothing increases by a factor of 2-3 in the range of original signal-to-noise of 5-20. Above the SNRlimit there is no change in the SNR. This is slightly less than the expected change in the SNR. In a simple circular average of radius=3 pixels, the SNR should increase by 5.3.
The SNR does not increase by a factor of 5.3 because not all pixels within the circular aperture are used, as they are not in the same location in PCA space as the pixel being smoothed.

If the smoothing is not done over a range of angular bins in PCA-space (Figure 2), or if $SNR_{enhanced} = SNR(x, y)$, then the FOM always increases by 1.0. The FOM increases because there are so few pixels with the PCA-space in the same bin and within the same spatial region. If the region is not restricted by a certain aperture, then the FOM increases only slightly. For example, if the radius is set to a value larger than the image, essentially including all the pixels in the analysis, then the FOM increases by only 0.8. This is much better than the simple radial average, which increases by orders of magnitude when the radius is the size of the image. Changing the region over which the PCA eigenspectra are determined scatters the eigenvalues, reducing the correlation between location in PCA-space and color. Using a larger region includes pixels with such high noise values due to sky, so that PCA results are scattered throughout the PCA-space. Using too small a region does not include a variation in color. For example, using the central bulge half-light radius includes almost no blue star formation colors.

3. Comparison with Other Methods

We compare PCA smoothing with other smoothing techniques: a simple circular smoothing kernel and Adaptsmooth (Zibetti, Charlot, Rix 2009). Adaptsmooth uses a circular aperture smoothing kernel, where the radius of the circle is set to achieve a SNR of 20.

Adaptsmooth (Zibetti, Charlot, Rix 2009) is compared to the PCA-smoothing technique for an area on the edge of an HII-like region of the mock galaxy. Adaptsmooth is run in default mode, where the radial aperture is determined by increasing the radius until the resulting SNR equals 20. Fixing the radius for all bands resembles the simple radial average results. Figures 4 and 5 show the FOM for Adaptsmooth. In almost all cases the FOM for Adaptsmooth is larger than the PCA-smoothing method presented here. When the FOM is calculated for the HII-like region, the results in 5 shows that Adaptsmooth has a FOM worse than no smoothing at all. This is due to Adaptsmooth mixing pixels with different colors, which will be demonstrated below.

Figure 8 shows a comparison between the $(g-r)$ color predicted by various smoothing methods versus the true color, for a pixel located on the edge of the spiral arm. For the simple circular smoothing kernel, an increase in the radius always produces a worse prediction of the color. The color is off by 0.1 mag at all radii greater than 2 pixels. Adaptsmooth picks a radius of 9 pixels for this pixel, as this was the maximum radius to reach a SNR=20 in the lowest SNR band ($z$-band). The radius of 9 pixels is so large that HII-like colors and redder disk colors get mixed together in the median. For PCA smoothing, with a best-fit Radius = 4, the predicted $g-r$ color (open circle at radius = 4pix) is within 1-sigma of the true value (red filled square) and has a lower noise level. Adaptsmooth (open triangle) is more than 3 sigma away from the true value.

The true $g$-band flux at the pixel in 8 is 152.782 DN. Adaptsmooth predicts a $g$-band flux of
127.30 DN, whereas the PCA-smoothing predicts a more accurate flux of 157.93 DN. The signal-to-noise for this pixel is 10.85, where the PCA-smoothed SNR = 28.63 versus the Adaptsmooth SNR = 36.73. There is clearly a trade off when considering the number of bins to use ($SNR_{enhanced}$), such that smoothing over more bins increases the SNR but decreases the accuracy of the predicted color and vice-versa for using fewer bins. The higher SNR for the Adaptsmooth result is due to over smoothing using too many pixels, which comes at the cost of a worse prediction of the SED ($g − r$ color in Figure 8). Figure 8 shows that the PCA-smoothing provides a better estimate of the true color, and has little dependence on the choice of radius.

Next, the effectiveness of each method to reproduce the stellar population of the mock galaxy are discussed. Maraston (2005) stellar population models are fit to the true (noise-free) mock galaxy image, mock galaxy image with no smoothing, a simple radially smoothed image, Adaptsmoothed image, and a PCA-smoothed image. The method uses a grid-search chi-squared minimization routine to find the best-fit model stellar population parameters, given the pixel’s $ugriz$-band fluxes and the model’s $ugriz$-band fluxes. For an aperture centered on the HII region, the noise-free truth image has an age of 7.5 Myr ($±$ 3.7 Myr). The simple radial smoothing has an age of 10.0 Myr ($±$ 1.0 Myr). Adaptsmooth results in ages of 6.0 Myr ($±$ 7.0 Myr). The PCA-smoothed results in an age of 7.0 Myr ($±$ 4.1 Myr). The PCA-smoothed result is a better description of the noise-free true age.

4. Case Study

4.1. NGC 450

Next PCA-smoothing is applied to real data sets. PCA-smoothing is first run on NGC 450, because it was also analyzed by Welikala et al. (2008). NGC 450 is a particularly interesting case because of the drastic variation in spatial colors. There is a flocculent spatial distribution of very blue star formation regions on top of a red disk. The PCA-smoothing was run on SDSS data of NGC 450 using the best-fit parameters determined in Section 2. After running the PCA-smoothing, stellar population models (Maraston 2005) are fit to the smoothed and un-smoothed data using a simple grid-search $\chi^2$ minimization routine. Figure 9 shows the results. Comparing the stellar population age maps with PCA-smoothing to unsmoothed maps shows that there is considerably more scatter in the un-smoothed maps. Figure 9 also shows that the PCA-smoothing preserves the structural information, where HII regions are still prominent in the PCA-smoothed image. The contrast between bright HII regions and a faint older disk is preserved during PCA-smoothing.

Figure 10 quantifies the level of scatter in the best-fit ages. Figure 10 shows the analysis for a region with lower SNR pixels which are located on the disk region. The scatter towards younger ages for un-smoothed data is clear. For unsmoothed data the best-fit ages range from 0.1 Gyr to 10 Gyr, where the PCA-smoothed analysis has best-fit ages clustered around a few Gyr to 9 Gyr. Since this is real data, the true age distribution is not known and is not shown.
4.2. SDSS J235106.25+010324.1

Next PCA-smoothing is run on SDSS J235106.25+010324.1, which has well defined blue spiral arms nearby a red bulge. Figure 11 shows the SDSS color image, the PCA map, PCA-smoothed g-band image, best-fit model age of the un-smoothed data, and best-fit model age of the smoothed data. The top middle panel of Figure 11 clearly shows that this method separates the bulge and spiral arms into different areas in PCA space, as can be seen by the bulge pixels being bright and the spiral arms being dark. The separation of spiral arms versus the bulge and inter-disk regions means that they will not be mixed in the PCA-smoothing routines.

5. Conclusions

This paper presents a method for smoothing SDSS data using a variation of Principal Component Analysis. The method is performed by running PCA simultaneously on multi-wavelength images of galaxies, and then smoothing over pixels that have similar locations in PCA space and spatial location within the galaxy. The advantages of the method are 1) no mixing of colors, 2) the method is geared towards stellar population analysis, 3) the parameters are tunable, and 4) the results are not extremely sensitive to the input parameters. The disadvantages of the method are 1) requiring initial analysis to identify the galaxy, 2) running PCA which may take computational time, and 3) requires well understood and uniform noise characteristic across different wavelengths. The smoothing parameters can be tuned to adjust the tradeoff between more smoothing and more color mixing versus less smoothing and more color purity. Increasing the $SNR_{enhanced}$ constant, results in an increased signal-to-noise of the smoothed pixel, at the cost of mixing over different colors. Lowering the $SNR_{enhanced}$ constant, results in a more pure color with less smoothing over different colors, at the cost of a lower smoothed signal-to-noise.

The method was tested and demonstrated using a mock galaxy with ugriz-band images having SNRs similar to that seen in typical SDSS data. Figures 1 and 4 show that the $FOM$ for the PCA-smoothing method is always better (lower), when compared to azimuthally symmetric smoothing routines. Considering Figures 5 and Figure 1, the best-fit parameters are $SNR_{max} = 30.0$, $Radius = 4.0$, $SNR_{enhanced} = 60.0$ and $SNR_{min} = 3.0$. The lack of extreme peaks in the $FOM$ shows the robustness of the method. Figures 1 and 4 imply that as long as the user doesn’t use extreme smoothing parameters, a reliable result will be obtained. Analysis of a region located on the boundary between an HII region and the red disk (Figure 8), shows that PCA smoothing is better at predicting a $(g-r)$ color to 0.2 mag, when compared to simple radial smoothing or Adaptsmooth.

The PCA-smoothing algorithm can be run on the SDSS data set, with the parameters described in this paper. The galaxies in the low-redshift NYU-VAGC (Blanton et al. 2005) would be perfect for analysis, as it includes galaxies within a comoving distance range of $10 < d < 150$ Mpc/h. These nearby galaxies are spatially resolved, and perfect for this type of analysis. This method is
geared towards large area surveys having multi-wavelength data, over a large part of the sky, and having uniform noise characteristics (i.e. COSMOS, DEEP, SDSS, 2MASS, DES). The method can also be applied to Galactic Nebulae as well, which are also asymmetrical extended objects with multi-wavelength data.
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Fig. 1.— The $g$-band and $r$-band images for the mock galaxy. The $g$-band image without noise (top left), $r$-band image without noise (top right), $g$-band image with noise (bottom left), $r$-band image with noise (bottom right). The $u, i, z$-band images are not shown. The images were made using a combination of GALFIT models and real data.
Fig. 2.— The first and second eigencoeficients for the pixels for the mock galaxy. For display purposes, pixels are color-coded according to their spatial location in the galaxy. PCA is run on the galaxy using the pixels within 2 half-light radii and having a SNR greater than 3. The right panel shows, the total Signal-to-Noise ratio versus the angle in PCA-space. Points are color-coded according to spatial position in the galaxy.
Fig. 3.— The noise-free mock galaxy $g$-band image (top-left), noisy $g$-band image (top-right), PCA-map of pixels associated by SNR and angle in eigencoefficient space (bottom-left), and $g$-band image smoothed with the method presented here (bottom-right). The star-formation region and bulge are in different locations in PCA-space, as can be seen in the PCA-map where the star-formation region is darker in color versus the lighter color bulge.
Fig. 4.— This figure shows the FOM versus the SNRmax, Radius, and SNRenhanced. The FOM for the PCA smoothed estimates (green-long dashed line, blue solid line) almost always has a lower FOM when compared to Adaptsmooth. This FOM is calculated for all the pixels within the quadrant of the galaxy shown in Figure 3. The smoothly varying nature of the FOM shows that this method is fairly robust to choice of input parameter. These panels show acceptable FOM values for Radii between 4-5 pixels, 30 < SNRmax < 50, and SNRenhanced > 40. Adaptsmooth has a fixed value of FOM in all the panels because Adaptsmooth is not a function of SNRmax or SNRenhanced, and the radius varies with position in the galaxy. For the region in Figure 4, Adaptsmooth uses different radii at different spatial location in the galaxy, which vary between 4 to 10 pixels.
Fig. 5.— The same as Figure 4 except for a region centered on the edge of an HII-like region. These panels show acceptable $FOM$ values for Radii between 2-4 pixels, $20 < SNR_{max} < 50$, and $SNR_{enhanced} > 60$. Adaptsmooth has a fixed value of $FOM$ in all the panels because Adaptsmooth is not a function of $SNR_{max}$ or $SNR_{enhanced}$, and the radius varies with position in the galaxy. For this region, Adaptsmooth uses different radii at different position, which vary between 9-10 pixels.

Fig. 6.— A map of pixels that are included in an average (green cross) for selected pixels (center pixel, star). The pixel in the center will have its flux replaced by an average over the pixels labeled with a green cross. The circle shows the best-fit radial aperture of $R=4$ pixels. Pixels with green crosses all have similar locations in PCA-space Figure 2.
Fig. 7.— The ratio of smoothed-to-original total SNR for the mock galaxy, for the best-fit parameters. This figure shows that this method provides more smoothing for pixels with lower SNR values.
Fig. 8.— This figure shows the comparison between different smoothing methods, for a single pixel located at the edge of the spiral arm. This figure shows the noise-free color of the mock galaxy or true color (solid red square), the color with Poisson noise due to sky and source added (green square), the PCA-smoothed color as a function of radius parameter (empty blue circles), the result of a Adaptsmooth (empty purple triangle), and the result of simple radial smoothing (solid black line).
Fig. 9.— A figure showing the SDSS color image (top left), the location in PCA-space (top center), the PCA-smoothed g-band image (top right), best-fit model age of the un-smoothed data (bottom left), and best-fit model age of the PCA-smoothed data (bottom right) for NGC450. Comparison of the bottom two panels shows that there is qualitatively less scatter in the PCA-smoothed age.
Fig. 10.— A histogram of the best-fit Maraston model age for a low SNR region of NGC450.
Fig. 11.— A figure showing the SDSS color image (top left), the location in PCA-space (top center), the PCA-smoothed g-band image (top right), best-fit model age of the un-smoothed data (bottom left), and best-fit model age of the PCA-smoothed data (bottom right) for SDSS J235106.25+010324.1. Comparison of the bottom two panels shows that there is qualitatively less scatter in the PCA-smoothed age.