



**HAL**  
open science

## Morphological classification of galaxies and its relation to physical properties

D. B. Wijesinghe, A. M. Hopkins, B. C. Kelly, N. Welikala, A. J. Connolly

► **To cite this version:**

D. B. Wijesinghe, A. M. Hopkins, B. C. Kelly, N. Welikala, A. J. Connolly. Morphological classification of galaxies and its relation to physical properties. *Monthly Notices of the Royal Astronomical Society*, 2010, 404 (4), pp.2077–2086. 10.1111/j.1365-2966.2010.16424.x . hal-01438893

**HAL Id: hal-01438893**

**<https://hal.science/hal-01438893v1>**

Submitted on 29 Sep 2021

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# Morphological classification of galaxies and its relation to physical properties

D. B. Wijesinghe,<sup>1</sup>\* A. M. Hopkins,<sup>2</sup> B. C. Kelly,<sup>3</sup>† N. Welikala<sup>4</sup> and A. J. Connolly<sup>5</sup>

<sup>1</sup>*School of Physics, A28, University of Sydney, NSW 2006, Australia*

<sup>2</sup>*Anglo-Australian Observatory, PO Box 296, Epping, NSW 1710, Australia*

<sup>3</sup>*Harvard-Smithsonian Center for Astrophysics, 60 Garden St, Cambridge, MA 02138, USA*

<sup>4</sup>*Laboratoire d'Astrophysique de Marseille, CNRS - Université Aix-Marseille, 38, rue F. Joliot-Curie, 13388 Marseille Cedex 13, France*

<sup>5</sup>*Department of Astronomy, University of Washington, Box 351580, Seattle, WA 98195-1580, USA*

Accepted 2010 January 26. Received 2010 January 20; in original form 2009 August 21

## ABSTRACT

We extend a recently developed galaxy morphology classification method, Quantitative Multi-wavelength Morphology (QMM), to connect galaxy morphologies to their underlying physical properties. The traditional classification of galaxies approaches the problem separately through either morphological classification or, in more recent times, analysis of physical properties. A combined approach has significant potential in producing a consistent and accurate classification scheme as well as shedding light on the origin and evolution of galaxy morphology. Here, we present an analysis of a volume-limited sample of 31 703 galaxies from the fourth data release of the Sloan Digital Sky Survey. We use an image analysis method called Pixel-z to extract the underlying physical properties of the galaxies, which is then quantified using the concentration, asymmetry and clumpiness parameters. The galaxies also have their multiwavelength morphologies quantified using QMM, and these results are then related to the distributed physical properties through a regression analysis. We show that this method can be used to relate the spatial distribution of physical properties with the morphological properties of galaxies.

**Key words:** galaxies: evolution – galaxies: formation – galaxies: general.

## 1 INTRODUCTION

The Hubble tuning fork (Hubble 1926) is one of the first and most widely used galaxy classification schemes. Even though it has provided many insights into the evolution of galaxies, their morphologies and other physical properties (van den Bergh 1998), it remains subjective, requiring experts to manually classify galaxies, and is not directly related to the physical properties of the galaxies. The use of one wavelength ( $\approx 450$  nm) also restricts the Hubble scheme, and studies such as Block & Wainscoat (1991) and Jarrett (2000) show clear examples of why a multiwavelength approach is vital for robust and thorough classification. Many galaxies have been discovered that simply do not fit into the Hubble scheme (van den Bergh 1976; Sandage & Brucato 1979). This is further exemplified at high redshift, where galaxies are at earlier stages of their evolution. The inclination of galaxies also plays a vital part in the classification process, especially for those galaxies that fall into the spiral sequence.

Galaxy classifications need to be compact and physically motivated and the above limitations have motivated a multitude of classification schemes to achieve these goals while addressing the various drawbacks of the Hubble tuning fork. de Vaucouleurs (1959) extended Hubble's scheme by introducing more divisions within classes. For instance, spirals were divided into more refined classes based on the presence of bars and rings around the galaxy and the spiral arms were divided into three new classes. The intrinsic basis of the Hubble system remains, though, limiting the utility of such schemes in progressing towards a connection between morphology and the underlying physical processes. Simpler classification systems by Morgan (1958, 1959) using the central concentration of light and a system based solely on the stellar population of galaxies by Morgan & Osterbrock (1968) have been successful at providing high discrimination of galaxies between classes. Kormendy & Bender (1996) aimed to revise the original classification of ellipticals by Hubble as this is mainly correlated to the inclination of galaxies rather than any intrinsic properties of the galaxies. These authors developed two main classes for ellipticals and several branches within each type. As a subjective scheme, however, the classes are not robust and many galaxies have properties that belong to multiple classes or none at all. Kormendy & Bender

\*E-mail: D.Wijesinghe@physics.usyd.edu.au

†Hubble Fellow.

(1996) attribute these inconsistencies to heterogeneous formation histories.

More recently automated classification schemes such as Artificial Neural Networks (ANNs) (Naim, Ratnatunga & Griffiths 1997a; Bazell 2000; Odewahn et al. 2002) have been used to accommodate the vast quantities of galaxies that require classification and to a large extent ANNs eliminate any subjective bias in the classification process, as well as being very accurate (Ball et al. 2004). ANNs cannot create a new classification system but rather replicate visual classification and with much higher consistency. These systems require a ‘test sample’ previously classified by a human expert on which to base classifications which has the disadvantage of allowing the same human biases and flaws of the classification system to propagate. The use of Self Organizing Maps by Naim, Ratnatunga & Griffiths (1997b), however, eliminates the need for a test sample and any human influence in the classification process.

Photometric decomposition techniques which analyse the observed distributions of photometric intensity (Peng et al. 2002; Simard et al. 2002) and Fourier analysis techniques that quantify luminosity distributions of galaxies (Trinidad 1998; Odewahn et al. 2002) have had moderate success in differentiating galaxies into their respective classes.

Non-parametric approaches such as the concentration, asymmetry and clumpiness (CAS) classification scheme have had success in objectively separating galaxies into Hubble’s classes as well as being applicable at high redshifts ( $z = 3$ ) (Abraham et al. 1996; Conselice 2003). The scheme uses three properties, concentration, asymmetry and clumpiness, which quantify aspects of galaxy morphology. These quantities identify formation histories, merging activity and areas of high star formation activity (Conselice 2003). This technique can be easily applied to the decomposition of the distribution of other physical properties in galaxies. The inclusion of additional parameters such as a Gini coefficient has been shown to produce more refined separations of galaxies but at the expense of increasing the dimensionality of the classification scheme (Lotz, Primack & Madau 2004; Lotz et al. 2006).

Classification of galaxies by physical properties alone has not been extensively carried out, although new techniques such as Pixel-z have emerged that enable the extraction of information about the physical properties of galaxies by fitting spectral energy distribution templates derived from stellar population evolution (Bruzual & Charlot 2002; Conti et al. 2003). Each pixel is fitted with templates, giving a localized analysis of the physical properties within the galaxy (Welikala et al. 2007, 2008, 2009).

Shapelet decomposition promises a new approach in the morphological classification of galaxies. Shapelets are Gaussian-weighted Hermite polynomials (Refregier 2003). They are also the eigenstates of the quantum harmonic oscillator (QHO) Hamiltonian, and are thus well understood (Refregier 2003). They have been shown to be useful in image simulation (Massey et al. 2004) and gravitational lensing measurements (Chang & Refregier 2002; Refregier & Bacon 2003). Shapelets use all the information about the shape of a galaxy and form a complete set thus making them an ideal candidate to be used in the morphological classification of galaxies (Kelly & McKay 2004). Shapelets are a central component in a new objectively developed and automated classification system known as the Quantitative Multiwavelength Morphology (QMM). QMM uses shapelets to decompose the galaxy images and a principal component analysis (PCA) to reduce the dimensionality of the data followed by Mixture-of-Gaussian models to objectively identify particular morphological classes of galaxies (Kelly & McKay 2004, 2005). Shapelets are not a compact form of classification and

require a PCA to account for this. The technique uses galaxy images in multiple filters, and currently images in the Sloan Digital Sky Survey (SDSS) filter set (*ugriz*) has been used. Kelly & McKay (2004) and Kelly & McKay (2005) show that this technique consistently reveals previously established relationships such as that between Hubble type and colour, as well as broad connections between morphology and the physical properties of galaxies.

We aim to identify relationships between the physical properties, measured with Pixel-z and quantified using CAS, and the morphological properties quantified using QMM.

## 2 QUANTIFICATION OF PHYSICAL PROPERTIES

Our initial objective is to extract the physical properties from galaxy images and then quantify the spatial distributions of these physical properties. The tools used for this process are Pixel-z (see Welikala et al. 2007, 2008, 2009), for extracting the physical properties, and CAS (Conselice 2003), to quantify their spatial distribution (the collective process will be known as Pixel-z : CAS herein).

These quantities are then compared with the results of the QMM analysis of the same galaxy images, through a regression analysis, to analyse how well QMM describes the spatial distribution of the physical properties in galaxies. This indicates the extent to which we can use QMM to connect physical and morphological properties of galaxies, providing us with the possibility of developing a comprehensive galaxy classification scheme that incorporates both physical and morphological properties of galaxies.

The data were obtained from the fourth data release (DR4) of the SDSS. The SDSS used a dedicated 2.5-m telescope located at Apache Point Observatory in New Mexico, USA together with a 142-megapixel camera in drift-scan mode to obtain images and spectroscopy over about a quarter of the sky (for more details, see York et al. 2000; Hogg et al. 2001; Smith et al. 2002; SubbaRao et al. 2002; Pier et al. 2003; Ivezić et al. 2004; Tucker et al. 2006)

### 2.1 Parametrization of Pixel-z output

Using the Pixel-z output from Welikala et al. (2008), we quantified the distribution of the physical properties in galaxies through the CAS technique developed by Conselice (2003). The CAS analysis uses the parameters concentration, asymmetry and clumpiness (C, A and S, Conselice 2003). We calculated these three parameters for four physical properties, age, star formation rate (SFR), colour excess and metallicity, each of which were obtained from the Pixel-z analysis of Welikala et al. (2008). The same process was carried out for the *r*-band (616.5 nm) image of the galaxy.

From the *r*-band CAS parameters, we can contrast the relationships between QMM and physical properties with that between QMM and the photometric distribution for the galaxies. The *r* band is convenient for this process as it lies in the middle of the SDSS filters and typically shows a high signal-to-noise ratio.

The concentration parameter is calculated from the ratio of the radii containing 20 and 80 per cent of the total flux. Asymmetry is derived from subtracting the image of a galaxy rotated by 180° from its original image. The clumpiness is quantified through the ratio of the flux in high spatial frequency structures within a galaxy to its total flux. These CAS parameters provide a morphological description of the physical properties of galaxies by quantifying their distributions derived from Pixel-z.

### 3 QUANTITATIVE MULTIWAVELENGTH MORPHOLOGY

QMM is a morphological classification method developed by Kelly & McKay (2004, 2005), using galaxy images observed through the five SDSS filters ( $u, g, r, i, z$ ). Our implementation of QMM involves two steps, shapelet decomposition and a PCA. The shapelet decomposition breaks down the image of the galaxy represented in all five filters into a set of mathematical functions which are quantified by a set of coefficients. To adequately reconstruct galaxy images the number of coefficients can be in the hundreds, so PCA is used to reduce the number of coefficients to a more manageable size. The outputs of the QMM analysis are the final PCA components, which encompass the majority of the variance in the data.

For the shapelet decomposition, 37876 galaxy images from the Pixel-z:CAS analysis were available, composed of the volume-limited sample analysed by Welikala et al. (2008, 2009). The resulting data set excluded 432 galaxies, the images for which contained numerous zero flux values that could not be processed in the PCA analysis. The sample was further restricted with an  $11\sigma$  cut on the variances in each dimension in order to ensure that the PCA was not compromised by outlying data points. The final sample for the QMM analysis consisted of 31 703 galaxies with images from all five filters and common to both the Pixel-z:CAS and QMM analysis.

The galaxies in the sample span a redshift range of  $0.00278 < z < 0.231$ . The analysis was first carried out over the entire redshift range. The analysis was then independently applied to four redshift bin subsamples containing approximately equal numbers

of galaxies. This approach allows us to identify possible biases due to the coarser spatial sampling of galaxies at progressively higher redshift, imposed by a fixed observational pixel scale, and identifying whether it is necessary to artificially redshift the galaxy images to mimic a common spatial sampling.

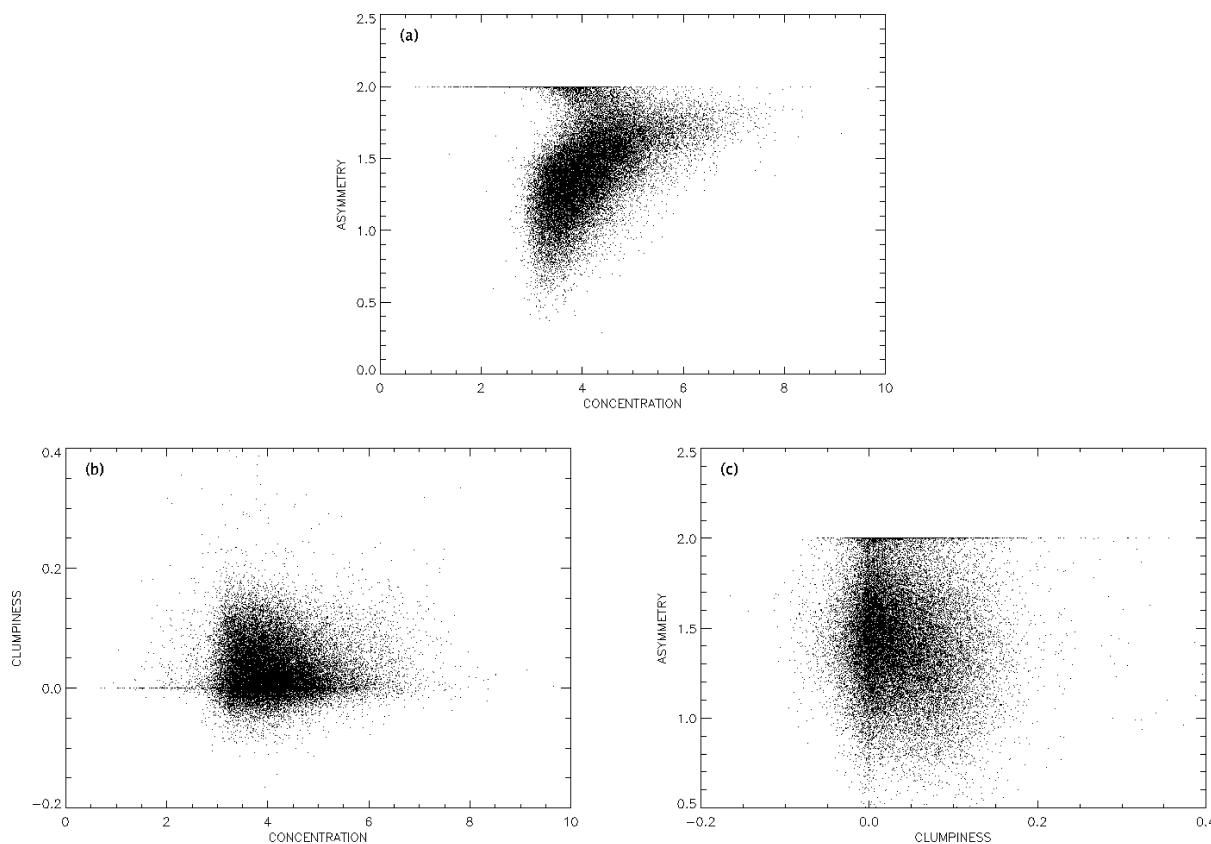
By comparing the results from QMM with those of Pixel-z:CAS, we can explore how QMM enables us to connect galaxy morphology with the underlying physical properties. The colour (or flux ratio) information encoded in the multiwavelength images used for this technique provides the key, as galaxy colours are a consequence of the combination of stellar evolutionary processes and multiple stellar populations. This suggests that there should be a direct connection between a quantitative morphology derived from multiwavelength images and the underlying properties of the stellar population within the galaxies. Therefore, we aim to determine the extent to which QMM is a reliable descriptor of the underlying physical properties of galaxies by comparing it with the results of the Pixel-z:CAS analysis.

## 4 RESULTS

### 4.1 Pixel-z: CAS

The CAS analysis provides morphology descriptions for the four sets of physical parameters from Pixel-z: age, SFR, colour excess and metallicity. For each of these the CAS parameters were measured.

Our results for the distribution of the SFR of galaxies in CAS space (Fig. 1) are not consistent with those found by Conselice (2003) for the photometric images. This is not unexpected, as this



**Figure 1.** Relationships between the three CAS parameters for the spatial distribution of SFR as inferred by Pixel-z, with (a) concentration against asymmetry, (b) concentration against clumpiness and (c) clumpiness against asymmetry.

is the first time that CAS has been applied to a distribution of physical rather than photometric properties. The ranges spanned by our CAS values are different, extending over a much larger range than those of Conselice (2003). The clumpiness parameter in particular (Figs 1b and 1c) shows a more restricted distribution than in Conselice (2003), with a number of systems having clumpiness very close to zero. The asymmetry parameter shows a maximum value of 2, a consequence of the mathematical definition of asymmetry.

Fig. 1(a) shows that at lower concentrations there is no relationship between concentration and asymmetry. As we move to higher concentrations, the asymmetries fall between 1.5 and the highest possible value of 2. At high asymmetries, the star formation activity is occurring only in highly localized regions of the galaxy. The proportion of light emanating from these regions within the galaxy compared to the central bulge is smaller than in a galaxy with a low asymmetry. This leads to a high concentration index.

Clumpiness is not correlated with concentration for SFR at any value. Fig. 1(b) shows uniform distribution above concentration = 3 and clumpiness = 0. A possible explanation for this could be that the clumpiness parameter takes into account the galaxy centres as well as the regions outside the centre. The clumpiness of the galactic centre would be expected to correlate positively with the concentration. The clumpiness outside the central regions would be expected to correlate negatively with the concentration, as the more clumpy the outer regions, the more localized the SFR activity. This leads to a higher concentration index as in the case of Fig. 1(a). When the clumpiness of both these regions are taken into consideration, we are more likely to see a large scatter. The lack of correlation between asymmetry and clumpiness seen in Fig. 1(c) has a similar explanation to that of Fig. 1(b).

The CAS distributions for other Pixel- $z$  physical properties also differ from those for the  $r$ -band light distribution of galaxies from Conselice (2003). Simply by analysing these relationships in CAS space, it is apparent that the distribution of physical parameters in galaxies does not mimic its photometric morphology in a trivial fashion. This highlights the fact that a simplistic approach to relating the single-filter photometric morphology (parametrized by CAS) with the distribution of physical properties within galaxies does not show any obvious connection. This in turn supports our motivation for using multiwavelength photometric information, through QMM, to relate galaxy morphology to the underlying physical properties.

The use of CAS in this investigation is not as a morphological indicator directly, but instead as a convenient technique for parametrizing the distributions of Pixel- $z$  physical parameters, to allow a comparison with the QMM results from the shapelet decomposition.

It is possible to use the differences in the physical parameters to refine the boundaries for the different galaxy classes set by Conselice (2003). For instance, Conselice (2003) set the CAS ranges for ellipticals to be concentration in the range  $4.4 \pm 0.3$ , asymmetry in the range  $0.02 \pm 0.02$  and clumpiness in the range  $0.00 \pm 0.04$ . As we use larger numbers of galaxies and at higher redshifts, these values will undoubtedly vary. If we use the four physical properties and their CAS boundaries for different galaxy types, it may be possible to set a more consistent limit for each class of galaxies. This extension of CAS to morphology classification based on physical properties could be a productive area for further investigation, but is beyond the scope of this paper.

Fig. 2 shows the relationship between the physical properties with regards to the asymmetry parameter. They allow for an understanding of how these properties affect each other and how they can be used to define classification criteria. Fig. 2(e) shows the best

agreement out of all the tested parameters as well as the strongest correlation. Both colour excess and metallicity agree with the SFR, but the correlation is weaker than that between colour excess and metallicity. The asymmetry in age does not match with the asymmetry in any of the other parameters but the tightness in the relationship between age and metallicity (Fig. 2f) has potential in being exploited to make finer cuts in the morphological classification. Strong relationships between these properties allow for establishing criteria for better galaxy classification than if used on their own.

The spread of galaxies at high asymmetries in Fig. 2 is highly constrained. High asymmetries indicate that the distribution of the various physical properties will be very ‘patchy’. As a result, these properties will be found in highly localized regions of each galaxy. As these properties have some relation to one another, it is likely that they will all be found in the same localized regions, resulting in highly asymmetric galaxies having high asymmetries for the measured attributes. This also explains the large distributions of galaxies at low asymmetries as the distribution of physical properties within the galaxy will not be ‘patchy’ allowing for the bigger spread in the physical properties across the galaxy. This spread will be largely independent of the other physical properties leading to lower correlations at low asymmetries.

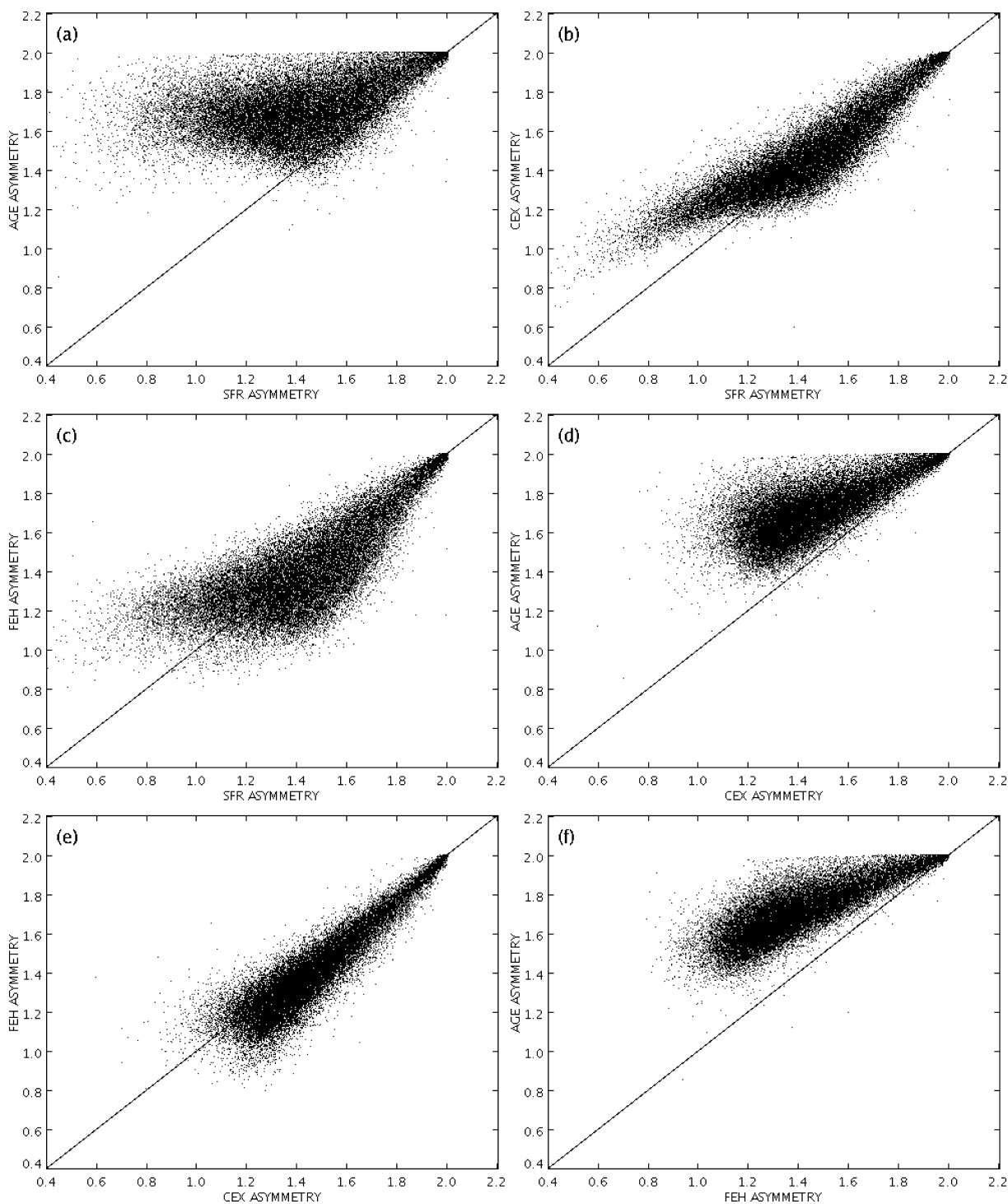
There is a limit of 2 for all the asymmetry parameters in Fig. 2. This is an artefact of the definition of asymmetry. Asymmetry is defined as the absolute value of the difference in flux between the original image and the same image rotated by  $180^\circ$ , divided by the flux of the original image. The maximum possible value for asymmetry that can be attained with this definition of asymmetry is 2.

## 4.2 QMM – principal components analysis

Performing the shapelet decomposition on the galaxy images using a shapelet order of 12 resulted in 91 coefficients per filter, making 455 coefficients per galaxy. A lower number of coefficients is insufficient to reproduce galaxy images reliably and even though a higher number of coefficients would have given a more accurate representation of the galaxy images it would have been too large to have been effectively reduced by the PCA.

A PCA was used to reduce the dimensionality of the results of the shapelet decomposition (Karhunen 1947; Loève 1978). To carry out the PCA, we first used the same procedure described in Kelly & McKay (2005) to calculate the shapelet coefficients, with two notable differences. As mentioned above, we do not artificially re-sample the images to the same redshift. Also, we use a singular value decomposition (SVD) technique similar to the one described in Berry, Hobson & Worthington (2004) to decompose the shapelet coefficients. The SVD accounts for the loss of orthogonality in the shapelets that result from the pixelization of the images. However, unlike Berry et al. (2004), the number of non-zero singular values is chosen in an objective manner. In our work, we chose the number of non-zero singular values to minimize the estimated squared error between the true galaxy image and the galaxy image reconstructed from the shapelet coefficients. We use Stein’s unbiased risk estimation to estimate this error (Stein 1981), which is easily calculated as a function of the number of non-zero singular values.

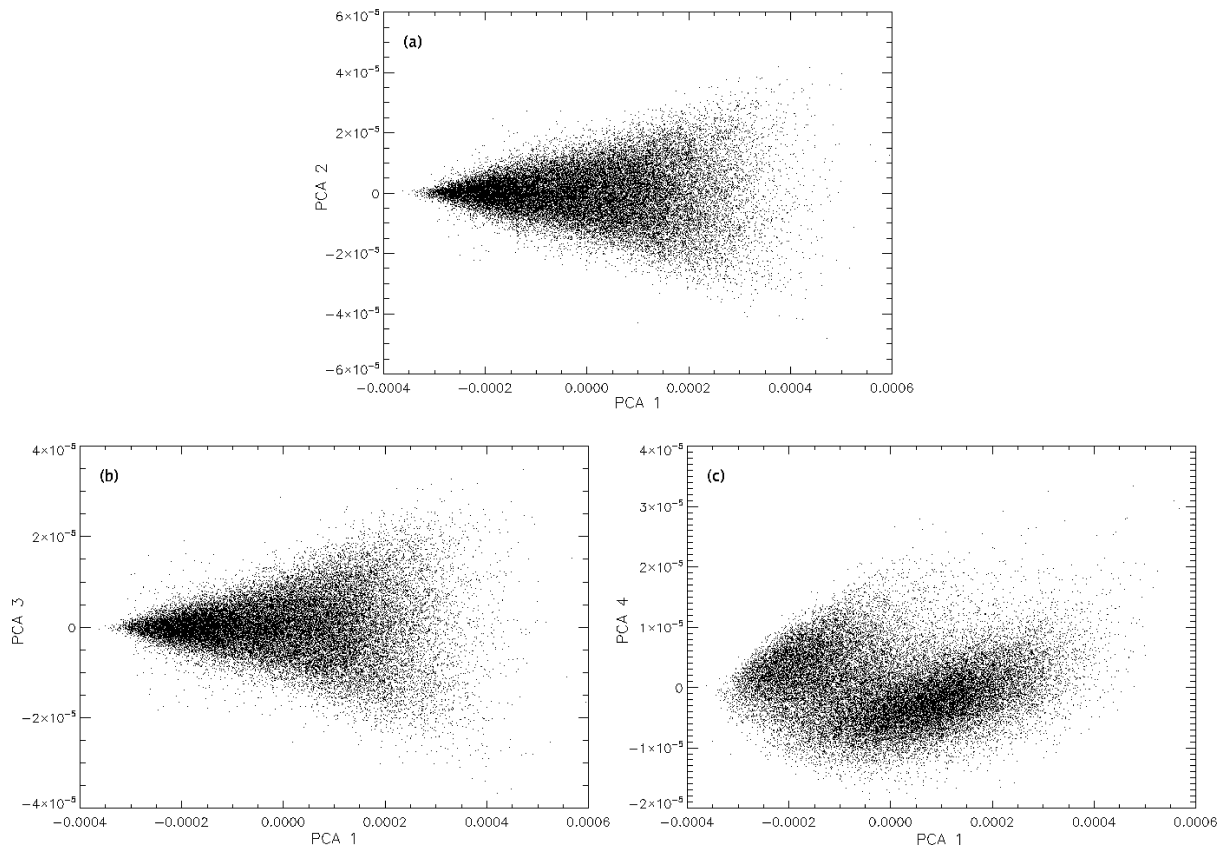
The first component contains the majority of the variance ( $\approx 75$  per cent) in the data set. Even though the subsequent components contain a much lower fraction of the variance, they are nevertheless important. The number of components was limited to eight, which contains 92.3 per cent of the total variance and is sufficient for our purposes.



**Figure 2.** Comparison of all physical properties against each other in the asymmetry parameter. Distributions are in the same ranges for ease of comparison and the line crossing each plot is the one to one relation. Figs (a), (b) and (c) compare the asymmetry of the SFR against the asymmetry of age, colour excess and metallicity, respectively. Figs (d) and (e) plot the asymmetry of colour excess with the asymmetry of age and metallicity while Fig. (f) compares the asymmetry of metallicity with age. The asymmetry of SFR, colour excess and metallicity follow each other to a large extent.

Discrimination between galaxy populations is not apparent in the first two panels of Fig. 3, but becomes clear in the third panel, plotting PCA 1 against PCA 4. This bimodality in galaxy morphology has long been known to exist and it is related to the two broad morphological classes of galaxies, early and late types. Kelly & McKay (2005) detected this same bimodality, in their PCA 1 against PCA 2.

The fact that this bimodality is seen here in a higher order PCA component could be a result of many factors. Kelly & McKay (2005) carried out the PCA using a sum-of-squares matrix while we used a covariance matrix. Also, even though we used a sigma cut to limit any extreme outliers, there may still be fewer distant outliers that can significantly affect the results of PCA. Thus, the location of the



**Figure 3.** Graphs for the first principal component against the next three. Note the different divisions shown. Components 2 and 3 have a diverging pattern while the fourth component has two clearly distinct groups. These results reproduce well those of Kelly & McKay (2005), but the separation for PCA 4 shown above was found for PCA 2 by Kelly & McKay (2005).

bimodality in PCA space does not reveal any fundamental property of galaxies as PCA is simply another way of representing the distribution of galaxies. The other separations in PCA space are very similar to the separations obtained by Kelly & McKay (2005).

Similarly, the galaxy types (or combination of them) that each PCA component represents will also depend on the above factors. To objectively identify particular classes contained within the PCAs, for a particular sample, one must apply Mixture-of-Gaussian methods (Kelly & McKay 2004, 2005) but this falls outside the aims of this experiment.

This analysis was reproduced for the subsamples split into redshift bins. The distributions of galaxies in PCA space in each of the redshift bins are similar to the analysis with the full sample. Furthermore, these distributions are consistent with each other (Fig. 4), as well as those of Kelly & McKay (2005). These distributions of galaxies in PCA space in each of the redshift bins fall within very similar ranges. These similarities among the different redshift bins allow us to conclude that our results are not strongly dependent on the treatment of the sample as a whole despite the range of redshift. Thus, there is no need to simulate a common redshift, through artificially redshifting the galaxy images by reducing their resolution, as implemented by Kelly & McKay (2005). The principal components for the redshift bin subsamples are also correlated against the Pixel-z:CAS measurements below, to identify any potential statistical differences.

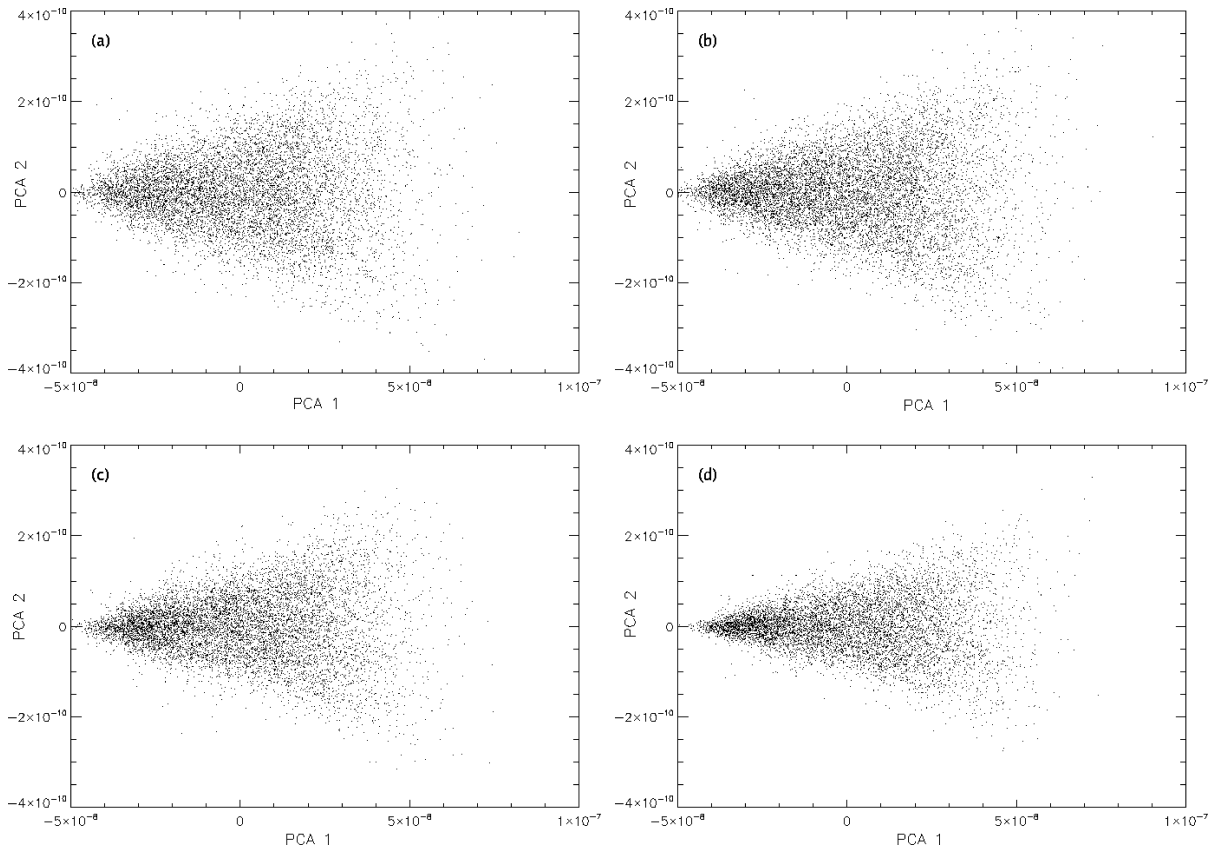
As with the Pixel-z: CAS analysis, our objective is not to define a classification system through the distribution of the QMM parameters of galaxies. Rather, we aim to identify relationships between

the two methods to identify the connection between the multiwavelength morphology and the spatial distribution of the underlying physical processes. The next step in our analysis is to quantify the relationships between the two methods.

## 5 CORRELATION ANALYSIS

Morphological classification alone provides a limited approach for understanding the properties and evolution of galaxies. Using just the physical properties may be more straightforward but these schemes do not address the origin or evolution of galaxy morphology. However, the multiwavelength nature of the recently developed QMM classification method provides an opportunity to connect morphological classification with underlying physical parameters. The colour information encoded in the multiwavelength images provides the key, as galaxy colours are a consequence of the combination of stellar evolutionary processes and multiple stellar populations. This suggests there should be a direct connection between a quantitative morphology derived from multiwavelength images and the underlying properties of the stellar population within the galaxies.

We have used Pixel-z and CAS as a way of quantifying several physical properties of galaxies so that they can be correlated with the QMM method, in order to identify how well QMM can represent the distribution of physical properties in galaxies. In order to connect the two methods, we carry out a regression analysis by performing a multiple linear regression fit to identify the extent to which QMM correlates with spatial distributions of physical



**Figure 4.** PCA for galaxies in the redshift bins. The distributions are very similar and a statistical analysis of these similarities is shown in Table 2.

properties in galaxies represented through the Pixel-z: CAS method. In an ideal case, we would find strong correlations between the tested parameters, but due to the large scatter seen in the above figures this is unlikely. For this reason, we focus on the relative correlations between the CAS parameters measured for the physical properties and the  $r$  band to observe whether any physical properties consistently show correlation coefficients higher than the  $r$ -band CAS parameters.

To do this, we carry out a regression analysis of the PCA components for each physical property against the CAS analysis of the  $r$ -band and  $u$ -band light distribution of the galaxy. The results are shown in Table 1 for the full sample and Table 2 for each of the smaller redshift range subsamples. The values in Tables 1 and 2 show the correlation coefficients between the distribution of each physical property in a galaxy (described by eight principal components) and the three CAS parameters. They also show the correlation coefficients between the  $r$ -band and  $u$ -band light distribution (also described by eight principal components) and the CAS parameters.

For this analysis, the CAS parametrization of the  $r$ -band images provides a convenient proxy for a single-filter derived morphology. Comparing the QMM results to the  $r$ -band CAS parameters, as well as to the Pixel-z: CAS output (physical properties), allows us to establish whether the QMM measurements contain more information about the distribution of physical properties within a galaxy than about the simple distribution of light.

If the correlation of the PCA components is higher for the CAS analysis of the physical properties compared to the  $r$ -band light profile, QMM would seem to be better at representing the spatial distribution of physical properties in galaxies than just their simple  $r$ -band light distribution. The regression analysis was carried out on the entire galaxy sample as well as independently for the redshift subsamples, in order to identify any systematic effect due to varying redshifts. The tables report the correlation coefficients between the PCA output and each of the CAS parameters for each property and for the  $r$ -band light distribution.

There is essentially no correlation between the concentration of the physical properties and the principal components, particularly

**Table 1.** Correlation coefficients between the CAS parameters and the distribution of physical properties in the galaxy (including the  $r$ -band and  $u$ -band light distributions).

CAS Parameters	Physical properties				Light profiles	
	Age	SFR	Colour excess	Metallicity	$r$ band	$u$ band
Concentration	0.04	0.01	0.02	0.03	0.20	0.04
Asymmetry	0.18	0.24	0.21	0.20	0.27	0.21
Clumpiness	0.30	0.46	0.43	0.46	0.28	0.40



**Table 2.** CAS parameter values for the physical properties across each redshift bin as well as the  $r$ -band light distribution.

Redshift range	CAS parameters	Physical properties				Light profiles	
		Age	SFR	Colour excess	Metallicity	$r$ band	$u$ band
$0.00278 \leq z < 0.066$	Concentration	0.05	0.16	0.04	0.04	0.23	0.05
	Asymmetry	0.20	0.27	0.23	0.23	0.30	0.21
	Clumpiness	0.26	0.46	0.42	0.44	0.24	0.37
$0.067 \leq z < 0.075$	Concentration	0.04	0.02	0.02	0.03	0.20	0.05
	Asymmetry	0.20	0.27	0.21	0.20	0.28	0.21
	Clumpiness	0.31	0.46	0.42	0.46	0.28	0.40
$0.076 \leq z < 0.083$	Concentration	0.22	0.02	0.20	0.03	0.19	0.06
	Asymmetry	0.18	0.24	0.20	0.18	0.26	0.21
	Clumpiness	0.32	0.47	0.43	0.47	0.36	0.39
$0.084 \leq z < 0.231$	Concentration	0.19	0.11	0.02	0.26	0.19	0.06
	Asymmetry	0.17	0.24	0.20	0.19	0.26	0.28
	Clumpiness	0.32	0.45	0.42	0.46	0.34	0.49

when these values are compared with the correlation for the  $r$ -band light distribution. The asymmetry of physical parameters has a slightly higher correlation with the output of QMM but even this is weaker than the correlation between QMM and the asymmetry of the  $r$ -band light distribution. Thus, the QMM morphology cannot describe the concentration and asymmetry of physical parameters better than it can describe the  $r$ -band light distribution.

The correlations between the physical properties in the clumpiness parameter and the QMM results are much higher than the correlation between QMM and the  $r$ -band light distribution. This indicates that the results of QMM provide a more accurate representation of the underlying physical parameter distribution, for the clumpiness parameter, than of the  $r$ -band light distribution of the galaxy. Thus, QMM, a morphology indicator, can represent the clumpiness measurement of physical properties of galaxies better than the single-filter photometric light distribution.

However, there is a possibility that the higher correlation we find between the clumpiness parameter and QMM output could be the result of noise in the  $u$ -band data from the SDSS images which was also processed by the QMM technique. This noise would make the image appear clumpy, hence providing a better correlation with the clumpiness parameter. On carrying out the correlation analysis with the QMM output and the  $u$ -band light distribution, it is apparent that clumpiness of the SFR, colour excess and metallicity still have a higher correlation with the QMM output than the  $u$ -band output. Thus, we can conclude that the correlation between the QMM output and the clumpiness of physical properties is not due to any noise in the  $u$ -band images and that QMM actually does represent the clumpiness of physical properties.

Following the analysis for the complete sample, the subsamples in redshift bins were analysed independently, with similar results, confirming that there is little or no systematic effect based on redshift (see Table 2).

For the separate redshift bins, all show similar patterns, and all are in agreement with the results for the complete sample. These results confirm that QMM is a better descriptor of the clumpiness of the physical properties compared to the  $r$ -band light distribution of the galaxies. For the concentration and asymmetry parameters, QMM cannot describe the distribution of the physical properties any better than it describes the  $r$ -band light distribution of the galaxies.

An important finding here is that the relative correlations between physical properties and the  $r$ -band light distributions are consistent

across all redshift ranges. The actual values between different redshifts vary, but they are still consistent with the findings from the complete sample. These fluctuations can be attributed to the fact that the redshift ranges themselves are not even. The two middle bins are particularly small compared to the two redshift ranges at the edges of the sample. The ranges were chosen such that the number of galaxies in each is equal, so as to ensure that the PCA is not biased by different sample sizes. Furthermore, the fluctuations do not display a trend with higher redshifts, indicating that there is no real systematic effect due to redshift. Thus, we conclude that QMM seems to provide a useful approach toward connecting galaxy morphologies to the morphologies of the physical parameters, and is independent of systematic effects due to redshift, over the small range considered here.

We stress that the correlation coefficients should not be taken as indicating real correlations. The correlation coefficients in all cases are too small to indicate any strong correlations between the tested parameters. Our goal is to compare the strength of the coefficients in relation to the  $r$  and  $u$  bands and identify those CAS parameters for the physical properties that have consistently higher correlations, if any, than in the  $r$  and  $u$  bands.

## 6 DISCUSSION

We have two main findings. The first is that the correlation between the results of QMM and the clumpiness of physical properties of Pixel- $z$ : CAS is significantly higher than the correlation with the clumpiness of  $r$ -band or  $u$ -band light distributions. For the concentration and asymmetry parameters, the correlation between QMM and the physical properties is much lower than the correlation with the  $r$ -band light distribution.

It is expected that the QMM results will be better correlated with the  $r$ -band light distribution of the galaxy as compared to the derived physical quantities as the QMM results are calculated from the light distribution of the galaxy. Thus, it is indeed significant that the QMM results are better correlated with the clumpiness of the derived physical properties than with the clumpiness of the  $r$ -band light distribution.

The lack of correlation in the concentration and asymmetry parameters is perhaps not completely unexpected. Neither of these parameters are particularly effective at describing the ‘patchy’ nature of the distribution of physical properties in galaxies. The Pixel- $z$

decomposition of the spatial distribution of various physical properties in galaxies (as seen in Welikala et al. 2008, 2009) is an excellent example of this type of distribution. Unlike the light profile of galaxies, physical properties are not necessarily centrally concentrated. As a consequence, it seems the concentration parameter is unlikely to be a useful descriptor for characterizing the distribution of physical properties of galaxies, particularly compared to the optical light distribution.

The asymmetry parameter may also not be effective at describing the ‘patchy’ distribution of physical properties, and it is further limited given that a centre of rotation needs to be identified. The brightest pixel was used as the centre of rotation, which is a reasonable approximation for the optical light distribution, but the light and physical properties do not share well-correlated distributions and the high spatial frequency nature of the physical properties means that asymmetry is probably not the best approach for quantifying these. Moreover, such ‘patchy’ distributions are inherently asymmetric, and many systems would show an asymmetry close to the maximum possible asymmetry value (asymmetry = 2). For these reasons, asymmetry, too, seems not to be a particularly useful parameter in describing the distribution of physical properties in galaxies.

Finally, there is the clumpiness parameter, which would clearly seem to be a more useful statistic in quantifying these ‘patchy’ distributions of physical properties of galaxies than the previous two, as it was developed to measure this type of distribution. The correlation coefficients measured do not indicate a real correlation, but we serve to distinguish the relative correlation strength of QMM with the Pixel-z: CAS measurements compared to  $r$  and  $u$  bands. The range of values of clumpiness is more likely to be encoding much more physical information about galaxies, rather than the less useful and potentially biased estimates for concentration and asymmetry. The QMM morphology should also be sensitive to the ‘patchy’ distributions of pixel colours that underlies the clumpy nature of the physical properties. This could well be the reason for the higher correlation values with QMM seen for clumpiness compared to the concentration and asymmetry as well as the clumpiness of the  $r$ -band light distribution. We also confirmed that this clumpiness is not due to any noise in the  $u$ -band images by showing that the correlation between the clumpiness parameters and QMM output is higher than that between the  $u$  band and the QMM output. This was true for all redshift bins as well. Using other approaches towards quantifying clumpy structure may be helpful in confirming this.

## 7 SUMMARY

We have compared two separate techniques for analysing galaxies, one using a purely physical approach (Pixel-z: CAS) and the other using a purely morphological approach (QMM). The purely physical approach uses the Pixel-z method to infer the distribution of four physical properties (age, SFR, colour excess and metallicity) within galaxies. These distributions were then quantified using the CAS method where each physical property was assigned a value for its concentration, asymmetry and clumpiness. This is the first application of CAS to distributed physical properties within galaxies. The Pixel-z: CAS procedure was also applied to the  $r$ -band and  $u$ -band light distribution. We did not discover a trivial relationship between the optical light distribution of galaxies and the distribution of the physical properties in CAS space. This places further significance on our objective of using QMM to connect the multiwavelength photometric morphology with the underlying physical properties.

This is not unexpected as CAS is able to be applied only to single-filter imaging, rather than a full multiwavelength morphology.

We also analysed the morphology of the galaxies using QMM where the images of the galaxies in five filters were decomposed using shapelets, followed by a PCA.

To measure the possible correlations between Pixel-z: CAS and QMM, we carried out a regression analysis for the CAS parameters of each physical property against the eight principal components and compared these to a similar analysis using the CAS parameters for the  $r$ -band and  $u$ -band light distributions. The regression analysis shows the extent to which the spatial distribution of physical parameters and QMM are related.

For the concentration and asymmetry parameters, no correlation was seen. Thus, QMM cannot describe the distribution of physical properties any better than it can describe the  $r$ -band light distribution for these two parameters.

The clumpiness of physical parameters is clearly connected better to QMM than is the clumpiness of the  $r$ -band or  $u$ -band light distributions. This shows that QMM (which was developed to quantify morphology) can describe at least some aspects of the distribution of physical properties better than the single-filter morphology of a galaxy. This demonstrates the fact that QMM incorporates physical properties as well as the morphology of galaxies through its inclusion of colour information.

Variation in redshift did not significantly affect the final results. The relative correlation between the QMM and physical properties, and QMM and the optical light distribution is consistent across all the redshift bins. The correlation between the QMM and physical properties, and QMM and the  $u$ -band light distribution was also consistent across all the redshift bins.

This is a significant step in the process of developing a complete galaxy classification scheme. The QMM approach is a useful technique that provides a new way of classifying galaxies. It may be more closely related to the underlying physical properties of a galaxy than traditional morphology measures.

This is the first time that there has been an attempt to combine the spatial distribution of physical properties and morphologies of galaxies. The results are promising, with a definite connection between the spatial distribution of physical properties and the morphology of the galaxies. This suggests that further investigation is warranted to explore the links between morphology and the underlying physical properties of galaxies.

## ACKNOWLEDGMENTS

We are grateful to the anonymous referee for positive and valuable comments. DBW acknowledges the support provided by the University of Sydney, School of Physics. AMH acknowledges support provided by the Australian Research Council through a QEII Fellowship (DP0557850). BCK acknowledges support from NASA through Hubble Fellowship grant #HF-01220.01 awarded by the Space Telescope Science Institute, which is operated by the Association of Universities for Research in Astronomy, Inc., for NASA, under contract NAS 5-26555. NW acknowledges support from the CNRS and the Agence Nationale de la Recherche (ANR). AJC acknowledges partial support from NSF grants 0851007 and 0709394.

## REFERENCES

Abraham R. G., Tanvir N. R., Santiago B. X., Ellis R. S., Glazebrook K., van den Bergh S., 1996, MNRAS, 279, L47

- Ball N. M., Loveday J., Fukugita M., Nakamura O., Okamura S., 2004, *MNRAS*, 348, 1038
- Bazell D., 2000, *MNRAS*, 316, 519
- Berry R. H., Hobson M. P., Worthington S., 2004, *MNRAS*, 354, 199
- Block D. L., Wainscoat R. J., 1991, *Nat*, 353, 48
- Bruzual G., Charlot S., 2003, *MNRAS*, 344, 1000
- Chang T., Refregier A., 2002, *ApJ*, 570, 447
- Conselice C. J., 2003, *ApJS*, 147, 1
- Conti A. et al., 2003, *AJ*, 126, 2330
- De Vaucouleurs G., 1959, *ApJ*, 130, 718
- Hogg D. W., Finkerbeiner D. P., Schlegel D. J., Gunn J. E., 2001, *AJ*, 122, 2129
- Hubble E., 1926, *ApJ*, 64, 321
- Ivezić Ž. et al., 2004, *Astron. Nachr.*, 325, 583
- Jarrett T. H., 2000, *PASP*, 112, 1008
- Karhunen K., 1947, Über lineare Methoden in der Wahrscheinlichkeitsrechnung. *Ann. Acad. Sci. Fennicae. Ser. A. I.*, 37, 1
- Kelly B. C., McKay T. A., 2004, *AJ*, 127, 625
- Kelly B. C., McKay T. A., 2005, *AJ*, 129, 1287
- Kormendy J., Bender R., 1996, *ApJ*, 464, L119
- Loève M., 1978, *Probability Theory. Vol. 2.* Springer-Verlag, New York
- Lotz J. M., Primack J., Madau P., 2004, *AJ*, 128, 163
- Lotz J. M., Madau P., Giavalisco M., Primack J., Ferguson H. C., 2006, *ApJ*, 636, 592
- Massey R., Refregier A., Conselice C. J., Bacon D. J., 2004, *MNRAS*, 348, 214
- Morgan W. W., 1958, *PASP*, 70, 364
- Morgan W. W., 1959, *PASP*, 71, 394
- Morgan W. W., Osterbrock D. E., 1969, *AJ*, 74, 515
- Naim A., Ratnatunga K. U., Griffiths R. E., 1997a, *ApJS*, 111, 357
- Naim A., Ratnatunga K. U., Griffiths R. E., 1997b, *ApJ*, 476, 510
- Odehahn S. C., Cohen S. H., Windhorst R. A., Philip N. S., 2002, *ApJ*, 568, 539
- Peng C. Y., Ho L. C., Impey C. D., Rix H. W., 2002, *ApJ*, 124, 266
- Pier J. R., Munn J. A., Hindsley R. B., Hennessy G. S., Kent S. M., Lupton R. H., Ivezić, Ž., 2003, *AJ*, 125, 1559
- Refregier A., 2003, *MNRAS*, 338, 35
- Refregier A., Bacon D., 2003, *MNRAS*, 338, 35
- Sandage A., Brucato R., 1979, *AJ*, 84, 472
- Simard L. et al., 2002, *ApJS*, 142, 1
- Smith J. A. et al., 2002, *ApJ*, 123, 2121
- Stein C. M., 1981, *Ann. Stat.*, 9, 1135
- SubbaRao M., Frieman J., Bernardi M., Loveday J., Nichol B., Castander F., Meiksin A., 2002, in Starck J.-L., Murtagh F. D., eds, *Proc. SPIE Vol. 4847, Astronomical Data Analysis II.* SPIE, Bellingham, p. 452
- Trinidad M. A., 1998, *Rev. Mexicana Astron. Astrofis.*, 7, 186
- Tucker D. L. et al., 2006, *Astron. Nachr.*, 327, 821
- van den Bergh S., 1976, *ApJ*, 206, 883
- van den Bergh S., 1998, *Galaxy Morphology and Classification.* Cambridge Univ. Press, Cambridge
- Welikala N., Connolly J. A., Hopkins A. M., Scranton R., Conti A., 2007, *AAS*, 39, 771
- Welikala N., Connolly A. J., Hopkins A. M., Scranton R., Conti A., 2008, *ApJ*, 677, 970
- Welikala N., Connolly A. J., Hopkins A. M., Scranton R., 2009, *ApJ*, 701, 994W
- York D. G. et al., 2000, *AJ*, 120, 1579

This paper has been typeset from a  $\text{\TeX}/\text{\LaTeX}$  file prepared by the author.