A cluster finding algorithm based on the multiband identification of red sequence galaxies

Masamune Oguri\(^1,2,3\)\(^\ast\)

\(^1\)Research Center for the Early Universe, University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan
\(^2\)Department of Physics, University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-0033, Japan
\(^3\)Kavli Institute for the Physics and Mathematics of the Universe (Kavli IPMU, WPI), University of Tokyo, Chiba 277-8583, Japan

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ABSTRACT

We present a new algorithm, CAMIRA, to identify clusters of galaxies in wide-field imaging survey data. We base our algorithm on the stellar population synthesis model to predict colours of red-sequence galaxies at a given redshift for an arbitrary set of bandpass filters, with additional calibration using a sample of spectroscopic galaxies to improve the accuracy of the model prediction. We run the algorithm on \(\sim 11960 \, \text{deg}^2\) of imaging data from the Sloan Digital Sky Survey (SDSS) Data Release 8 to construct a catalogue of 71743 clusters in the redshift range \(0.1 < z < 0.6\) with richness after correcting for the incompleteness of the richness estimate greater than 20. We cross-match the cluster catalogue with external cluster catalogues to find that our photometric cluster redshift estimates are accurate with low bias and scatter, and that the corrected richness correlates well with X-ray luminosities and temperatures. We use the publicly available Canada-France-Hawaii Telescope Lensing Survey (CFHTLenS) shear catalogue to calibrate the mass-richness relation from stacked weak lensing analysis. Stacked weak lensing signals are detected significantly for 8 subsamples of the SDSS clusters divided by redshift and richness bins, which are then compared with model predictions including miscentring effects to constrain mean halo masses of individual bins. We find the richness correlates well with the halo mass, such that the corrected richness limit of 20 corresponds to the cluster virial mass limit of about \(1 \times 10^{14} \, h^{-1} M_\odot\) for the SDSS DR8 cluster sample.

Key words: galaxies: clusters: general

1 INTRODUCTION

Clusters of galaxies have been known to be a useful probe of the Universe. The mass distribution of clusters is mostly determined by the dynamics of dark matter, which makes it easier to compare with theoretical predictions based on N-body simulations (e.g., Navarro et al. 1997; Jing & Suto 2002). Recent extensive gravitational lensing analyses have convincingly shown that both the radial density profile (Umetsu et al. 2011; Oguri et al. 2012, Coe et al. 2012; Newman et al. 2013a; Okabe et al. 2013) and the degree of non-sphericity (Oguri et al. 2010, 2012) of massive clusters are in good agreement with expectations based on the standard Λ-dominated cold dark matter model, possibly except for the dark matter distribution at the very centre where baryonic effects play a significant role (Newman et al. 2013a). Clusters of galaxies are also thought to be one of main probes of dark energy in future surveys (see Weinberg et al. 2013, for a review), particularly given the well-understood mass distribution.

Clusters of galaxies can be identified in many different wavelengths. For instance, massive clusters of galaxies have efficiently been identified in X-ray images (e.g., Ebeling, Edge, & Henry 2001; Böhringer et al. 2004), because the gas in clusters of galaxies is heated by gravitational infall to emit thermal bremsstrahlung radiation. The hot gas in clusters also scatters cosmic microwave background (CMB) photons to distort the CMB spectrum at millimetre and submillimeter wavelengths. This Sunyaev-Zel’dovich (SZ) effect is rapidly becoming an efficient way to construct a large sample of clusters, especially at high redshifts (e.g., Reichardt et al. 2013; Hasselfield et al. 2013). A disadvantage of X-ray and SZ cluster surveys is a lack of redshift information. Hence these cluster samples should be complemented by optical or near-infrared data for redshift estimates of individual clusters.

* E-mail: masamune.oguri@ipmu.jp
Thanks to recent developments of wide-field optical surveys, large catalogues of clusters are being constructed in optical wavelengths. While finding clusters in single band optical imaging data (e.g., Abell 1958) is challenging given the low number density contrast of galaxies, one can identify clusters much more easily and securely by utilizing multi-band optical data (e.g., Gladders & Yee 2000; Liu et al. 2008; Miller et al. 2014; Murphy, Geach, & Bower 2012; Jian et al. 2014). Furthermore, multi-band optical cluster selection usually provides good photometric redshifts of clusters, and thereby enables to construct three-dimensional cluster catalogues.

Many applications of these cluster catalogues, including constraints on cosmological parameters (e.g., Vikhlinin et al. 2009; Mantz et al. 2014; Rozo et al. 2010), require knowledge of scaling relations between observables and masses of clusters. Stacked weak lensing provides a powerful means of accurate calibration of such scaling relations (e.g., Johnston et al. 2007; Leauthaud et al. 2011; Ford et al. 2014; Covone et al. 2014). In particular, we can use the same imaging data for both identifying clusters and weak lensing mass calibrations in wide-field optical surveys. In these surveys, by measuring a mean tangential shear profile around a sample of clusters, we can accurately constrain the average mass of the cluster sample (Sheldon et al. 2009; Oguri & Takada 2011; Rozo, Wu, & Schmidt 2011). This can be regarded as another advantage of selecting clusters of galaxies in optical wavelength. A caveat is that the orientation bias of optically selected clusters can lead to the overestimation of the average mass by up to $\sim 5\%$ (Dietrich et al. 2013).

In this paper, we present a new optical cluster finding algorithm. The algorithm, which we name CAMIRA (Cluster finding algorithm based on Multi-band Identification of Red-sequence gAlaxies), is essentially a red-sequence method, and has a flexibility to allow us to use an arbitrary set of filters. For this purpose, we base our algorithm on the stellar population synthesis (SPS) model. The SPS model, after appropriate calibrations to improve the accuracy, is used to predict colours and stellar masses of red-sequence galaxies. Then each galaxy in the image is fitted to the SPS model to compute the likelihood of being a red-sequence galaxy at a given redshift. The use of only the red-sequence galaxies is because it is expected to reduce the scatter in the mass-richness relation (Rozo et al. 2010; Rykoff et al. 2012). Our method also implements an algorithm for finding the brightest cluster galaxy (BCG) and takes account of masking effects. Our algorithm is similar to the recently published redMaPPer method (Rykoff et al. 2014; Rozo & Rykoff 2014) in several ways, though we note that our algorithm is developed mostly independently of redMaPPer.

We apply our method, CAMIRA, to the Sloan Digital Sky Survey (SDSS; York et al. 2000) data to construct a cluster catalogue in the redshift range $0.1 < z < 0.6$. Specifically we use imaging data from the SDSS Data Release 8 (DR8; Alhara et al. 2011) which covers more than 10000 deg$^2$ of the sky. There have already been many algorithms that were applied to the SDSS data to produce large cluster catalogues (Goto et al. 2002; Miller et al. 2005; Koester et al. 2007; Dong et al. 2008; Wen, Han, & Liu 2009; Szabo et al. 2011; Wen, Han, & Liu 2012; Hao et al. 2009, 2010; Rykoff et al. 2014; Rozo & Rykoff 2014), suggesting that the SDSS dataset is ideal for developing and testing new algorithms. Another advantage of the SDSS is the availability of a large number of spectroscopic measurements of red galaxies, which are in our algorithm used to calibrate the SPS model. We then use various X-ray data as well as the public Canada-France-Hawaii Telescope Lensing Survey (CFHTLens; Heymans et al. 2012) shear catalogue to test and characterize our SDSS cluster catalogue.

The outline of this paper is as follows. In Section 2, we describe our cluster finding algorithm in detail. Section 3 presents our cluster catalogue in the SDSS DR8. Section 4 describes testing of the algorithm mostly using X-ray data. We also conduct weak lensing analysis of the SDSS cluster sample in Section 5. In Section 6, we summarize our results. The SDSS DR8 cluster catalogue is presented in Appendix A. Throughout the paper we adopt the standard $\Lambda$-dominated flat cosmological model with the matter density $\Omega_M = 1 - \Omega_L = 0.28$, the dimensionless Hubble constant $H_0 = 0.7$, the baryon matter density $\Omega_b = 0.042$, the spectral index $n_s = 0.96$, and the normalization of the matter fluctuation $\sigma_8 = 0.8$.

2 ALGORITHM

2.1 Modelling red-sequence galaxies

We use the SPS model of Bruzual & Charlot (2003) to model the spectral energy distribution of red-sequence galaxies. The advantage of using the SPS model is that one can easily compute colours in an arbitrary combination of filters, which is essential for multi-band selections of red-sequence galaxies as considered in this paper. Throughout the paper we assume the Salpeter initial mass function.

The SPS model characterizes the properties of galaxies by several parameters, including the age of the galaxy, star formation history, metallicity ($Z$), the stellar mass ($M_*)$, and the dust extinction. Our basic strategy is to adjust these parameters to reproduce the observed colours of red-sequence galaxies, and use the model for calculating the likelihood of galaxies being in the red-sequence as a function of redshift. While complicated models contain more degrees of freedom to calibrate the SPS model to reproduce observed red-sequence colours, here we adopt a rather simple model with a single instantaneous burst at the formation redshift $z = z_f$ and no dust extinction, as the model appears to be already good enough to model the red-sequence (see below).

The colour-magnitude diagram of red-sequence galaxies is known to exhibit the so-called “tilt”, i.e., the galaxy colours change slightly as a function of magnitude, which originates from the mass dependence of metallicity (Kodama & Arimoto 1997; Stanford, Eisenhardt, & Dickinson 1998). We include the tilt by assuming the following functional form for metallicity:

$$\log Z_{\text{SFS}} = \log Z_{11} + aZ \left[ \log (M_{\text{star}}/10^{11} M_\odot) \right] ,$$

(1)

where $M_{\text{star}}$ is the input stellar mass, or put another way, the total stellar mass formed at $z_f$, and $Z_{11}$ specifies the normalization of metallicity, i.e., $Z_{11}$ is metallicity of galaxies with $M_{\text{star}} = 10^{11} M_\odot$. The input stellar mass $M_{\text{star}}$ in
general differs from the stellar mass at the age considered, \( M_* \), because a fraction of the total stellar mass originally formed is converted to gas as a consequence of stellar evolution. For technical reasons, throughout the paper we use \( M_{*,\text{in}} \) rather than \( M_* \) as a model parameter.

We determine the model parameters \( z_f, \log Z_{11}, \alpha_z \), by examining colour-magnitude diagrams in several massive clusters. Specifically, we choose \( z_f = 3, \log Z_{11} = -2, \) and \( \alpha_z = 0.15 \), which are found to reproduce observed colour-magnitude relations of cluster member galaxies in the SDSS data reasonably well.

It is known that the colour-magnitude relation involves an intrinsic scatter. We model the intrinsic scatter by the scatter of the metallicity. Again, based on the examination of colour-magnitude relations for SDSS clusters, we adopt the scatter of \( \sigma_{\text{log}Z} = 0.14 \) to model the intrinsic scatter. We also restrict the stellar mass range when fitting, \( M_{*,\text{min}} < M_* < M_{*,\text{max}} \). Here we set log(\( M_{*,\text{max}}/M_\odot \)) = 13.5 and log(\( M_{*,\text{min}}/M_\odot \)) = 9.5, which cover the stellar mass filter range introduced below.

### 2.2 Calibrating colours

The SPS model predicts red-sequence galaxy colours reasonably well, but is never perfect. Therefore it is essential to calibrate galaxy colours using observed colours of galaxies with spectroscopic redshifts.

In this paper, we quantify the likelihood of each galaxy being red-sequence galaxies at redshift \( z \) by the following chi-square

\[
\chi^2 = \sum_{i=1}^{N_{\text{fil}}} \frac{(m_{i,\text{obs}} - m_{i,\text{SPS}} - \delta m_{i,\text{resi}})^2}{\sigma_{i,\text{obs}}^2 + \sigma_{i,\text{resi}}^2} + \frac{(\log Z_{11} - \log \bar{Z}_{11})^2}{\sigma_{\text{log}Z}^2}
\]

where \( i \) runs over photometric bands of the galaxy catalogue, \( N_{\text{fil}} \) is the total number of photometric bands, \( m_{i,\text{obs}} \) and \( \sigma_{i,\text{obs}} \) are observed magnitude and its error in the \( i \)-th band, \( m_{i,\text{SPS}} \) is the SPS model prediction at redshift \( z \), and log(\( \bar{Z}_{11} \)) = -2 and \( \sigma_{\text{log}Z} = 0.14 \) (see Section 2.1 for details). In addition, \( \delta m_{i,\text{resi}} \) and \( \sigma_{i,\text{resi}} \) are included to account for the imperfectness of the SPS model.

Our SPS model is calibrated by estimating \( \delta m_{\text{resi}} \) and \( \sigma_{\text{resi}} \) as a function of rest-frame wavelength and redshift. For each spectroscopic galaxy, we minimize \( \chi^2 \) by varying \( Z_{11} \) and \( M_{*,\text{in}} \). We then fit residuals of magnitudes for a sample of spectroscopic galaxies as a function of rest-frame wavelength \( \lambda \) and redshift \( z \). Specifically, we divide the sample into different redshift bins, and in each redshift bin \( z_j \) we fit the residuals to polynomials in \( \lambda \):

\[
\delta m_{\text{resi,fit}}(\lambda, z_j) = \sum_{i=1}^{n_f} a_i(z_j)(\lambda - \lambda_0)^i,
\]

with \( a_i(z_j) \) being polynomial coefficients. Throughout the paper we fix \( \lambda_0 = 5000 \) \( \text{A} \). We then construct smooth functions of polynomial coefficients \( a_i(z) \) as a function of redshift by the spline interpolation.

The scatter \( \sigma_{\text{resi}} \) describes the scatter of spectral energy distributions of red-sequence galaxies that is unaccounted in our SPS model. We divide magnitude residuals of the spectroscopic galaxies into rest-wavelength bins and compute a scatter in each bin with a weight of \( 1/(\sigma_{\text{obs}}^2 + \sigma_{\text{resi}}^2) \) for each residual. In this procedure we also remove 2.5\( \sigma \) outliers. In each bin, this calculation is performed iteratively until the value of \( \sigma_{\text{resi}} \) converges. The bin size of \( \Delta \lambda = 400 \) \( \text{A} \) is adopted.

In order to minimize the effect of outliers, such as spectroscopic galaxies that are outside the red-sequence, we iteratively compute \( \delta m_{\text{resi}} \) and \( \sigma_{\text{resi}} \). In the first round, we compute \( \chi^2 \) with \( \delta m_{\text{resi}} = \sigma_{\text{resi}} = 0 \), but only include galaxies with best-fit metallicity of \(-1.65 < \log Z_{11} < -2.35\), corresponding to 2.5\( \sigma \) in the metallicity scatter. We then repeat the calculation of \( \chi^2 \) including residuals and scatters estimated in the previous pass and refine these by using galaxies with \( \chi^2 < \chi^2_{\text{max, resi}} \) for residual fitting and \( \chi^2 < \chi^2_{\text{max, resi}} \) for estimating their scatter, with \( \chi^2_{\text{max, resi}} = 4 \) and \( \chi^2_{\text{max, resi}} = 20 \) throughout this paper. The second pass is repeated twice to further refine the residual estimate.

Equation (2) does not include the off-diagonal element of the covariance matrix of model magnitude errors. In practice, we expect some correlated model errors between different bands, but we assume that those correlated errors are taken care of by including metallicity in the model fitting, because shifting metallicity systematically changes colours of red-sequence galaxies. Put another way, our working assumption is that correlated errors of magnitudes of red-sequence galaxies between different bands can be modelled by the scatter of metallicity which is included in our fitting procedure. Indeed, we check residual distributions of spectroscopic galaxies for the calibration and find no significant correlations between residuals of different bands, which supports our working assumption.

### 2.3 Constructing a richness map

For red-sequence galaxies, \( \chi^2 \) computed by equation (2) at the galaxy redshifts should obey the \( \chi^2 \) distribution with \( \nu = N_{\text{fil}} - 1 \) degrees of freedom:

![Figure 1. The \( \chi^2 \) distribution dp/\( \chi^2 \) (equation 4 solid line) and the number parameter \( n_\nu(\chi^2) \) (equation 5 dashed line) as a function of \( \nu \). The number parameter \( n_\nu(\chi^2) \) is multiplied by 0.1 for illustrative purpose. The degree of freedom of \( \nu = 4 \) is assumed.](image)
The filter is normalized as
\[
\frac{dp_\nu}{d\chi^2} = \frac{1}{2^{\nu/2}\Gamma(\nu/2)} e^{-\chi^2/2} (\chi^2)^{\nu/2-1},
\]
where \(\Gamma(x)\) denotes the Gamma function. Bearing this in mind, we define cluster galaxy “number” parameter \(n_\nu(\chi^2)\) as
\[
n_\nu(\chi^2) = \frac{2^{3\nu/4}}{\nu^{\nu/2}U(\nu/4, 1/2, \nu^2/8)} e^{-(\chi^2)^2/2},
\]
with \(U(a,b,x)\) being the confluent hypergeometric function of the second kind. The normalization of \(n_\nu(\chi^2)\) is chosen so as to satisfy
\[
\int_0^\infty n_\nu(\chi^2) \frac{dp_\nu}{d\chi^2} d\chi^2 = 1.
\]
Thus when we sum up \(n_\nu(\chi^2)\) over \(N_{\text{mem}}\) cluster member galaxies we expect to have
\[
\sum_{i=1}^{N_{\text{mem}}} n_\nu(\chi^2) = N_{\text{mem}} \int n_\nu(\chi^2) \frac{dp_\nu}{d\chi^2} d\chi^2 = N_{\text{mem}}.
\]
We show \(dp_\nu/d\chi^2\) and \(n_\nu(\chi^2)\) in Figure 1. In reality galaxy catalogues contain non-member galaxies. The contribution of these non-members is negligible if they have large enough \(\chi^2\), i.e., \(\chi^2 \gg \nu\), but in practice foreground and background galaxies can make non-negligible contributions to the sum of \(n_\nu(\chi^2)\). We account for this by subtracting the background level, as we will describe in more detail below.

We count the number of member galaxies in a specific stellar mass range. The lower mass limit should correspond to \(\sim 0.2L_\odot\) because it was shown to be optimal in terms of richness measurements (Rykoff et al. 2012). The upper mass limit is also important to reduce possible projection effects in selecting member galaxies. Thus we choose our stellar mass filter as
\[
F_M(M_{*,\text{in}}) = \exp \left[ -\left( \frac{M_{*,\text{in}}}{M_\odot} \right)^4 - \left( \frac{M_1}{M_{*,\text{in}}} \right)^4 \right],
\]
where \(M_\odot = 10^9 M_\odot\) and \(M_1 = 10^{10.2} M_\odot\) are adopted in this paper.

The number of member galaxies should be counted within some aperture that roughly corresponds to radii of clusters of our interest. On the other hand, the background level must be subtracted to correctly estimate richness. The background level, however, is not uniform but has large-scale structure. A compensated filter estimates the background level in an annulus just outside the aperture, and hence properly takes account of the non-uniformity of the background. In this paper, we adopt spatial filter of the following functional form:
\[
F_R(R) = \frac{\Gamma\left[n/2, (R/R_0)^2\right] - (R/R_0)^n e^{-(R/R_0)^2}}{\Gamma(n/2, 0)}.
\]
The filter is normalized as \(F_R(0) = 1\). The filter \(F_R(R)\) with different values of \(n\) are plotted in Figure 2. Throughout the paper we adopt \(n = 4\) and a fixed scale radius \(R_0 = 0.8 h^{-1}\) Mpc in physical unit. While a possible extension of our algorithm is to include the richness dependence of the scale radius (e.g., Rykoff et al. 2012), here we adopt the fixed scale radius for simplicity.

Now we can construct a richness map by adding up the number parameter with a weight of these filter functions
\[
N_{\text{mem}}(\theta, z) = \sum_i \frac{1}{f_{\text{mask}}} n_\nu(\chi^2_i; \theta_i, z) F_M(M_{*,i}) \times F_R(D_A|\theta_i - \theta|),
\]
where
\[
N_{\text{mem}}(\theta, z) = \sum_i \frac{1}{f_{\text{mask}}} n_\nu(\chi^2_i; \theta_i, z) F_M(M_{*,i}) \times F_R(D_A|\theta_i - \theta|),
\]
f_{\text{mask}} = \begin{cases} f_{\text{mask,c}} & (F_R(D|\theta_i - \theta)| > 0), \\ f_{\text{mask,b}} & (F_R(D|\theta_i - \theta)| < 0), \end{cases}
\quad (12)

f_{\text{mask,c}} = \frac{\int_{F_R > 0} d\theta' S(\theta') F_R(D|\theta' - \theta)}{\int_{F_R > 0} d\theta' F_R(D|\theta' - \theta)},
\quad (13)

f_{\text{mask,b}} = \frac{\int_{F_R < 0} d\theta' S(\theta') F_R(D|\theta' - \theta)}{\int_{F_R < 0} d\theta' F_R(D|\theta' - \theta)}. \quad (14)

When the masking area is too large, \( f_{\text{mask}} \ll 1 \), the richness estimate becomes highly uncertain. Thus we impose minimum values on both \( f_{\text{mask,c}} \) and \( f_{\text{mask,b}} \) below which the richness map is masked. We adopt the minimum values of 0.6 and 0.2 for \( f_{\text{mask,c}} \) and \( f_{\text{mask,b}} \), respectively.

2.5 Refining cluster candidates

We identify cluster candidates from peaks in the three-dimensional richness map, \( N_{\text{mem}}(\theta, z) \). We then refine redshift and richness estimates of each peak as follows.

First we sort the cluster candidate list in descending order of the peak richness. For each peak at \( \theta = \theta_p \), we start with refining the cluster redshift estimate. Following Rykoff et al. (2014), we obtain a new cluster redshift by maximizing the following likelihood

\[
\ln L_z = -\frac{1}{2} \sum_i w_i \chi_i^2(\theta_i, z) \Theta [F_R(D|\theta_i - \theta_p)],
\quad (15)
\]

where the summation runs over galaxies (each located at \( \theta_i \)). The weight \( w_i \) is introduced so that we only use high significance cluster member galaxies for estimating the cluster redshift. It is defined as

\[
w_i = \frac{1}{1 + \exp \left( -n_{\text{th}} - n_{\text{mem},i}/\sigma_n \right)},
\quad (16)
\]

where \( n_{\text{mem},i} \) is the number parameter for each galaxy

\[
n_{\text{mem},i} = \frac{1}{f_{\text{mask}}} n_{\nu}(\chi_i^2; \theta_i, z) F_M(M_{\nu,i}) F_R(D|\theta_i - \theta_p),
\quad (17)
\]

and \( n_{\text{th}} \) is defined such that

\[
\sum_{n_{\text{mem},i} > n_{\text{th}}} f_{\nu} N_{\text{mem}}(\theta_p, z).
\quad (18)
\]

We adopt \( f_{\nu} = 0.5 \) and \( \sigma_n = 0.05 \). The weight \( w_i \) becomes close to 1 and 0 for large and small number parameters, respectively. The new cluster redshift \( z_{cl} \) is the redshift that maximizes the likelihood defined by equation (15).

Next we identify the BCG of the cluster. For each galaxy at \( \theta = \theta \), we compute the likelihood of being the BCG by fixing the redshift to \( z_{cl} \)

\[
\ln L_{\text{BCG}} = -\frac{\log(M_{\text{BCG}}/M_\odot)}{2\sigma_{\log M}} + \ln n_{\nu}(\chi^2) - \frac{R_1^2}{\sigma_R^2},
\quad (19)
\]

where \( \chi^2 \) and \( M_{\text{BCG}} \) are best-fit \( \chi^2 \) and \( M_{\text{BCG}} \) for redshift \( z = z_{cl} \), respectively, and \( R_1 = D_A(z_{cl}|\theta_i - \theta_p) \) is the physical distance between the peak and the galaxy. The first term in the right-hand side of equation (19) aims at selecting massive (bright) galaxies as a BCG candidate. The second terms simply indicates the BCG should be a cluster member galaxy at high significance. The last term is introduced to assure that the position of the BCG is not too far from the peak of the richness map. The parameters in these terms should be chosen empirically so as to select the BCG effectively. In this paper we tentatively assume \( \log(M_{\text{BCG}}/M_\odot) = 12.3 \), \( \sigma_{\log M} = 0.3 \), and \( \sigma_R = 0.3 \text{h}^{-1}\text{Mpc} \). The likelihood function (equation 19) and the parameters in have been determined rather empirically, and are subject to improvements by careful analysis of cluster centring. Also the so-called “blue BCGs” will not be efficiently selected by this algorithm because we impose the condition that the BCG be a red-sequence galaxy (\( n_{\nu}(\chi^2) \) in equation 19).

Once the BCG candidate is obtained, we again estimate the cluster redshift via equation (15) replacing the peak position \( \theta_p \) with the candidate BCG position \( \theta_{\text{BCG}} \). With the refined cluster redshift \( z_{cl} \) we again search for the BCG which maximizes the likelihood defined by equation (19). This procedure is repeated until the solution converges. Finally we define the richness of this cluster by \( N_{\text{mem}} \) (equation (11) computed at the BCG position \( \theta_{\text{BCG}} \) and redshift \( z_{cl} \), i.e.,

\[
N_{\text{mem}} = N_{\text{mem}}(\theta_{\text{BCG}}, z_{cl}).
\]

After the final cluster candidate is obtained, we percolate the catalogue to ensure that no cluster is multiply counted. For each galaxy we assign a weight factor \( w_{\text{mem}} \) that scales similar to a membership probability as

\[
w_{\text{mem}} = n_{\nu}(\chi^2) F_M(M_{\nu,i}) F_R(D|\theta_i - \theta_{\text{BCG}}),
\quad (20)
\]

for \( F_R > 0 \), and \( w_{\text{mem}} = 0 \) for \( F_R < 0 \). In the examinations of lower richness peaks the number parameter of these galaxies are multiplied by an additional factor of \( 1 - \sum w_{\text{mem}} \) in order to avoid double counting of cluster member galaxies. Galaxies with \( \sum w_{\text{mem}} \geq 1 \) are not used in the subsequent analysis.

3 CLUSTER CATALOGUE IN SDSS DR8

3.1 Data

We apply our cluster finding algorithm CAMIRA to imaging data of SDSS DR8 (Aihara et al. 2011). The input galaxy catalogue include model magnitudes (MODEL_MAG) and their errors for SDSS ugriZ-band. We exclude galaxies with any of the following flags: SATURATED, SATUR_CENTER, BRIGHT, and DEBLENDENAD_MOVING. We only use galaxies with extinction-corrected i-band magnitude brighter than 21.0 and its error smaller than 0.2. The dust extinction map of Schlegel, Finkbeiner, & Davis (1998) is used for the Galactic extinction correction. We use all galaxies in the RA ranges between 310 and 50 deg and between 110 and 270 deg and the Dec range between −11 and 69 deg, which fully cover the main survey regions of SDSS both in the North and South Galactic Caps.

In the SDSS footprint there are several bad regions, such as regions near bright stars and nearby galaxies, where the photometric calibration contains some problems. In this paper we do not mask these regions. Therefore, for some applications of the cluster catalogue, such as angular clustering measurements, one may have to apply additional masks to remove these bad regions.

3.2 Calibration

We use spectroscopic galaxy catalogues from the BOSS DR10 (Ahn et al. 2014) as well as SDSS DR7.
Figure 3. The number distribution of SDSS spectroscopic galaxies, which are used for the colour calibration, as a function of redshift. Three peaks at $z \sim 0.1$, $z \sim 0.35$, and $z \sim 0.5$ correspond to typical redshifts of SDSS main galaxy sample ( Strauss et al. 2002 ), SDSS luminous red galaxy sample ( Eisenstein et al. 2001 ), and BOSS CMASS galaxy sample ( Dawson et al. 2013 ), respectively. See Section 2.2 for details.

(Abazajian et al. 2009) for the calibration of galaxy colours as described in Section 2.2. Since we are interested in red-sequence galaxies, we apply a rough colour cut

$$g - r > \begin{cases} 0.6 + (5/3)z_g & (z_g < 0.3), \\ 1.1 & (z_g > 0.3), \end{cases} \quad (21)$$

$$g - r < 4.0, \quad (22)$$

$$r - i > 0.3, \quad (23)$$

$$u - g > 1.6 \quad \text{for} \quad z_g < 0.25, \quad (24)$$

where $z_g$ denotes a spectroscopic redshift of each galaxy. The calibration process ( Section 2.2 ) is performed iteratively to remove contributions from outliers, and hence the colour cut here is intended to remove only obvious non red-sequence galaxies. We use 1152403 galaxies after the colour cut to calibrate galaxy colours, adopting the order of $n_f = 5$ for the polynomial fitting ( equation 3 ). The redshift bin width is $\Delta z = 0.02$, and the calibration is done for the redshift range of $0.02 < z < 0.82$. The redshift distribution of these spectroscopic galaxies is shown in Figure 3. We show resulting residuals $\delta m_{\text{res,fit}}$ ( equation 4 ) as well as scatter $\sigma_{\text{res}}$ in Figure 4.

As a sanity check, we derive “photometric redshifts” of these spectroscopic galaxies by finding redshifts that minimize $\chi^2$ defined by equation 2, after the calibration of galaxy colours as described above, and compare them with their spectroscopic redshifts. Figure 5 shows the comparison of the photometric redshifts $z_{\text{photo}}$ with the spectroscopic redshifts $z_{\text{spec}}$ from the SDSS and BOSS. The Figure indicates that our model, once the calibration is properly done, recovers true redshifts very well. To quantify the accuracy of the photometric redshifts, we compute the mean $\delta_z$ and the scatter $\sigma_z$ of residuals $(z_{\text{photo}} - z_{\text{spec}})/(1 + z_{\text{spec}})$, with $3\sigma$ clipping to exclude the effect of outliers. We find $\delta_z = 0.0020$ and $\sigma_z = 0.0230$, which are sufficiently good for our purpose.
3.3 Richness correction

The magnitude-limited nature of imaging surveys suggests that the richness estimate can be incomplete particularly at high redshifts. In the case of SDSS, the smooth stellar mass cut at \( M_\ast \sim M_l \sim 10^{10.2} M_\odot \) (see equation 8) indicates that the richness estimate is nearly complete only at \( z \lesssim 0.25 \). Here we provide a scheme to empirically correct for the richness incompleteness as a function of redshift.

First for each redshift we derive the stellar mass function \( d\phi/dM_\ast \) of red-sequence galaxies by summing up the number parameter \( n_\nu (\chi^2) \) (equation 5) for individual stellar mass bins. The stellar mass function is constructed solely from the data, i.e., we do not assume any functional form for the stellar mass function. Note that this stellar mass function is truncated at low-mass end due to the stellar mass filter (equation 8) at low redshifts, but at higher redshifts the stellar mass function is truncated at higher stellar masses due to the magnitude limit of the input galaxy catalogue. We thus derive the lower stellar mass cutoff \( M_\ast,\text{cut} (z) \) of the stellar mass function as a function of redshift. Then the richness correction factor \( f_N (z) \) is computed as

\[
f_N (z) = \frac{\int_{M_\ast,\text{cut}(z)}^{\infty} d\phi/dM_\ast,\text{in}(z_{\text{ref}}) dM_\ast,\text{in}}{\int_{0}^{\infty} d\phi/dM_\ast,\text{in}(z_{\text{ref}}) dM_\ast,\text{in}},
\]

where \( z_{\text{ref}} \) is a reference redshift where the stellar mass function should be sampled down to \( M_l \). In this paper we adopt \( z_{\text{ref}} = 0.1 \). The richness correction is applied simply by dividing the original richness by the correction factor

\[
\hat{N}_{\text{cor}} = \frac{\hat{N}_{\text{mem}} \cdot f_N (z_{cl})}{f_N (z_{cl})}.
\]

\[
(26)
\]

Figure 6 shows the richness correction factor \( f_N (z) \) for the SDSS cluster sample.

3.4 Cluster catalogue

We construct our SDSS DR8 cluster catalogue in the redshift range \( 0.1 < z_{cl} < 0.6 \) and the richness range \( \hat{N}_{\text{cor}} > 20 \). The catalogue contains 71743 clusters (see Appendix A). The total area that satisfies the masking criteria shown in Figure 7 is \( \sim 11960 \text{ deg}^2 \). Figure 7 shows the footprint of our cluster catalogue. As expected, the spatial distribution shows large-scale structure. We also show the richness and redshift distributions in Figures 8 and 9, respectively. The cluster abundance is a steep function of the richness \( \hat{N}_{\text{cor}} \), which is expected from the steep mass dependence of the cluster abundance. Before the richness correction \( f_N (z) \) is applied, the redshift distribution begins to decrease quickly at \( z \sim 0.4 \) where the incompleteness of richness estimates due to the magnitude limit of SDSS gets significant (see Figure 6). After the richness correction, the cluster number count monotonically increases out to \( z \sim 0.6 \), which is qualitatively consistent with the trend expected for a volume-limited cluster catalogue.

For more quantitative discussions, we compute the comoving number density of the clusters as a function of cluster, which is shown in Figure 10. When the uncorrected richness \( \hat{N}_{\text{mem}} \) is used as a threshold, the number density indeed...
The cluster redshift $z_{cl}$ as a function of cluster redshift $z$. The comoving number density distribution of the Figure 10. The histogram of the cluster redshift $z_{cl}$ for our SDSS cluster catalogue. The solid line shows the histogram for the whole cluster catalogue, whereas the dashed line is the histogram for clusters with the uncorrected richness $N_{mem} > 20$.

4. TESTING THE PERFORMANCE

4.1 External catalogues

We compare the CAMIRA SDSS DR8 cluster catalogue with other cluster catalogues in order to better understand and characterize our cluster catalogue. For this purpose we largely follow Rozo & Rykoff (2014) to adopt several public X-ray cluster catalogues, which are briefly summarized below.

The XMM Cluster Survey (XCS; Mehrtsens et al. 2012) is a serendipitous search for galaxy clusters using the XMM-Newton Science Archive. The catalogue contains 503 clusters. Spectroscopic redshifts and X-ray temperature $T_X$ are available for nearly half of these clusters. We use only clusters with spectroscopic redshifts for comparisons.

The Meta-Catalogue of X-ray detected Clusters of galaxies (MCXC; Piffaretti et al. 2011) is based on publicly available ROSAT All-Sky Survey (RASS; Voges et al. 1999) as well as serendipitous cluster catalogues. There are 1559 clusters in total. In this catalogue the X-ray luminosity $L_X$ is consistently defined in the $0.1 - 2.4$ keV band integrated within $R_{200c}$, the radius within which the interior average density becomes 500 times the critical density of the Universe.

The ACCEPT cluster catalogue (Cavagnolo et al. 2009) consists of X-ray clusters observed with Chandra. We adopt X-ray temperature $T_X$ and redshift measurements for 239 X-ray clusters from the catalogue.

In addition, we use the spectroscopic redshifts of optical clusters from the Sloan Giant Arcs Survey (SGAS) just for the redshift comparison. Specifically we use spectroscopic redshifts of 24 SGAS clusters reported in Bayliss et al. (2011), Oguri et al. (2012), and Bayliss et al. (2014). For each cluster, the cluster redshift is accurately estimated from spectroscopy of $\gtrsim 30$ member galaxies.

In order to compare these external catalogues with our CAMIRA cluster catalogue, we need to match clusters between these catalogues. We consider a simple matching criterion that clusters that are within $1 \ h^{-1} \text{Mpc}$ in the physical transverse distance and redshift difference $\Delta z < 0.1$ are matched. When there are several matching candidates, we match clusters with smallest angular separations. Note that this simple matching procedure can fail in some rare cases, which we ignore in the following analysis.

4.2 Cluster redshifts

First we check the accuracy of cluster redshift $z_{cl}$, which is estimated based on photometric data only in our algorithm (see Section 2.3), with spectroscopic redshifts of clusters from all the external catalogues described above. There are 483 clusters in total for the comparison. The result shown in Figure 11 clearly indicates that our cluster redshift is quite accurate with small outlier rate. We quantify the accuracy again by calculating the bias $\delta_z$ and scatter $\sigma_z$ of residuals $(z_{cl} - z_{\text{catalog}})/(1 + z_{\text{catalog}})$ with 3$\sigma$ clipping, finding $\delta_z = 0.003$ and $\sigma_z = 0.009$, which is comparable to the accuracy achieved by, e.g., redMaPPer (Rozo & Rykoff 2014).
indicates that ACCEPT clusters appear to have larger X-ray temperatures than XCS clusters. This is also evident from Figure 13, which shows a similar comparison for X-ray luminosities \( L_X \) for MCXC clusters. The solid and dashed lines show the best-fit \( L_X - \hat{N}_{\text{cor}} \) relation and 1σ scatter, respectively. The lower panel shows the residual of fitting as a function of cluster redshift \( z_{cl} \).

### 4.3 Comparison with X-ray properties

The comparison between richness and X-ray properties such as X-ray luminosity \( L_X \) and temperature \( T_X \) is useful because these X-ray properties are thought to correlate better with cluster masses than optical richness. This suggests that the tightness of the mass-richness relation can be inferred from the scaling relation between richness and X-ray properties. For instance, Rozo \& Rykoff (2012) has used this approach to refine their richness estimates. Here we compare our richness estimates with external X-ray cluster catalogues described above in a manner similar to Rozo \& Rykoff (2014).

Figure 12 compares corrected richness \( \hat{N}_{\text{cor}} \) and X-ray luminosities \( L_X \) for MCXC clusters. The plot shows clear positive correlation between \( \hat{N}_{\text{cor}} \) and \( L_X \). We fit the relation assuming a linear relation in logarithmic space,

\[
\log \left( \frac{L_X}{10^{44} \text{erg s}^{-1}} \right) = a_L \log \left( \frac{\hat{N}_{\text{cor}}}{50} \right) + b_L,
\]

(27)

using the least square method. We find the best-fit slope \( a_L = 1.58 \pm 0.09 \) and normalization \( b_L = 0.32 \pm 0.02 \). The 1σ scatter in \( \log L_X \) is 0.35 without any outlier rejections. Figure 12 indicates that residuals of the fitting show no strong correlation with cluster redshift.

Figure 13 shows a similar comparison for X-ray temperature \( T_X \) for XCS and ACCEPT clusters. Again, \( T_X \) correlates well with richness \( \hat{N}_{\text{cor}} \). Assuming the scaling relation of the form

\[
\log \left( \frac{T_X}{\text{keV}} \right) = a_T \log \left( \frac{\hat{N}_{\text{cor}}}{50} \right) + b_T,
\]

(28)

we find the best-fit slope \( a_T = 0.76 \pm 0.06 \) and normalization \( b_T = 0.70 \pm 0.01 \). Again residuals show no strong trend with cluster redshift.

As discussed in Rozo \& Rykoff (2014), there is a systematic offset between X-ray temperatures of XCS and ACCEPT clusters. This is also evident from Figure 13 which indicates that ACCEPT clusters appear to have larger X-ray temperatures for a given richness. We fit each cluster sample to equation (28), and find \( a_T = 0.61 \pm 0.13 \), \( b_T = 0.62 \pm 0.03 \), and the scatter of 0.14 for XCS clusters, and \( a_T = 0.51 \pm 0.07 \) and \( b_T = 0.76 \pm 0.01 \), and the scatter of 0.10 for ACCEPT clusters. Our result indicates ≈ 40% systematic offset of X-ray temperatures, which is consistent with Rozo \& Rykoff (2014). Rozo \& Rykoff (2014) argued that the temperature offset can be ascribed to differences of X-ray temperature definitions between ACCEPT and XCS clusters, and therefore is not problematic.

In comparison with results presented in Rozo \& Rykoff (2014), we find that the CAMIRA cluster catalogue and richness estimate are comparable to the redMaPPer cluster catalogue in terms of the tightness of cluster richness with X-ray properties. The scatter in the scaling relations translates into the scatter of the mass-richness relation of \( \sigma_{\ln M} \approx 0.3 \) – 0.4 (i.e., scatter of \( \sim 0.15 \) for \( \ln M \)). While the slight increase of the comoving number density at higher redshift (see Figure 10) implies enhanced scatter of the mass-richness relation at \( z \gtrsim 0.35 \), it is not very clear in this analysis using X-ray. In fact the scatter may be affected by the incompleteness of X-ray catalogues we use for the comparisons. X-ray data are available only for massive clusters, which is particularly true for high-redshift clusters, and hence less X-ray luminous clusters are not included in deriving the scaling relation. This Malmquist bias can lead to an underestimation of scatters as well as systematic shifts of mean relations. Therefore more careful comparisons with X-ray properties

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**Figure 11.** Comparison between photometric cluster redshifts \( z_{cl} \) (see Section 2.5) and spectroscopic redshifts of clusters from various external catalogues. See Section 4.1 for descriptions of individual external catalogues.

**Figure 12.** Comparison between corrected richness \( \hat{N}_{\text{cor}} \) and X-ray luminosities \( L_X \) for MCXC clusters. The solid and dashed lines show the best-fit \( L_X - \hat{N}_{\text{cor}} \) relation and 1σ scatter, respectively. The lower panel shows the residual of fitting as a function of cluster redshift \( z_{cl} \).
should take account of the sample incompleteness, which we leave for future work.

For a further test, we also conduct the “X-ray mass scatter” analysis presented in Rozo & Rykoff (2014). This is done by scrambling the richness values for the matched cluster catalogue, re-fit the richness temperature relation, and derive the scatter for this shuffled catalogue. We create 1000 realizations of the shuffled cluster catalogues for both XCS and ACCEPT clusters. We find average scatters of 0.17 and 0.13 for XCS and ACCEPT clusters, respectively, which should be compared with 0.14 and 0.10 for unshuffled XCS and ACCEPT clusters, respectively. Therefore the scatter is indeed reduced relative to the shuffled richness catalogue. For all the shuffled cluster samples, their scatters are larger than those of the unshuffled cluster samples, which indicate that the reduction of the scatter is more than 3σ significant. This is again comparable to the performance of redMaPPer (see Rozo & Rykoff 2014).

Figure 14. Completeness as a function of X-ray temperature (dashed) or luminosity (solid) threshold, for matched cluster sample at $0.1 < z < 0.5$. In order to compare the result with that presented in Rozo & Rykoff (2014), here we use an approximate treatment to determine which X-ray clusters fall within the optical mask, which leads to an underestimate of the completeness.

4.4 Completeness

Here we conduct a simple completeness estimate using the external X-ray catalogues, following the procedure given in Rozo & Rykoff (2014). First we need to know whether any given X-ray clusters fall within the footprint of the CAMIRA SDSS DR8 catalogue. We adopt an approximated approach that X-ray clusters that fall within 40′ of any clusters in the CAMIRA SDSS DR8 catalogue are within the footprint. Note that this procedure tends to underestimate the completeness, but this allows us to compare our result with that presented in Rozo & Rykoff (2014). Then we derive the completeness as a function of X-ray luminosity and temperature thresholds. We use clusters in the redshift range $0.1 < z < 0.5$, the same range adopted in Rozo & Rykoff (2014).

Figure 14 show the completeness from cross-matching with XCS, ACCEPT, and MCXC clusters. We find that the completeness is quite high, > 0.9 for X-ray luminous and high temperature clusters. The high completeness is indeed comparable to redMaPPer result (see Rozo & Rykoff 2014). The completeness is less than unity at the high $T_X$ and $L_X$ end, due to the approximate treatment to determine which X-ray clusters fall within the optical mask as mentioned above (see also Figure 9 of Rozo & Rykoff 2014).

In this analysis we did not explicitly match the comoving volume density. At low redshifts, $z \lesssim 0.35$, the comoving number densities of CAMIRA and redMaPPer cluster catalogues are similar, but at higher redshifts the CAMIRA cluster catalogue has much higher number density of clusters than redMaPPer. However, we note that even if we restrict the redshift range to $0.1 < z < 0.3$ the completeness is similar to that plotted in Figure 14.

4.5 Offsets between optical and X-ray cluster centres

Finding cluster centres is one of the most important challenges in optical cluster finding algorithms. As X-ray emissions trace the gravitational potential of galaxy clusters, comparisons of centres of optically selected clusters with X-ray centres of same clusters provide a useful means of test-
Ing the accuracy of the centring algorithm of optical cluster
finders.

As in Rozo & Rykoff (2014), for each matched X-ray cluster we compute a physical transverse distance between optical and X-ray cluster centres to derive the offset distribution. Figure 15 shows the offset distributions both for XCS and ACCEPT clusters. We find that the offset is generally small, but the distribution has a long tail to large offsets. The distribution of the offset $R$ is often modelled by the two component Gaussian distributions (e.g., Johnston et al. 2006; Oguri & Takada 2011)

$$p(R) = \frac{f_{\text{cen}}}{R_{s,\text{cen}}} \exp \left( -\frac{R^2}{2R_{s,\text{cen}}^2} \right) + (1-f_{\text{cen}}) \frac{1}{R_s} \exp \left( -\frac{R^2}{2R_s^2} \right).$$

(29)

Figure 15 plot an example of the two-component model with $f_{\text{cen}} = 0.7$, $R_{s,\text{cen}} = 0.05h^{-1}\text{Mpc}$, and $R_s = 0.42h^{-1}\text{Mpc}$, which very roughly explains to the observed distribution. Given the critical importance of miscentring of optical cluster
ter samples for, e.g., stacked weak lensing analysis (see below), it is important to examine the offset more carefully using larger samples of X-ray clusters.

5 WEAK LENSING MASS CALIBRATION

5.1 Measurement

Here we employ a public shear catalogue of the CFHTLenS (Heymans et al. 2012) to calibrate the mass-richness relation. The CFHTLenS shear catalogue is based on a sophisticated Bayesian galaxy shape measurement with careful calibrations using simulated galaxy images (Miller et al. 2013). The photometric redshift estimate is also available for each galaxy (Hildebrandt et al. 2012). Readers are referred to Erben et al. (2013) for more details of the public shear catalogue.

The shear catalogue provides two ellipticity components ($e_1$, $e_2$) in the celestial coordinate system as well as multiplicative and additive calibration factors $m$ and $c_2$ for each galaxy. For each reference centre, we compute the tangential ellipticity component as

$$e_+ = -e_1 \cos 2\phi - (e_2 - c_2) \sin 2\phi,$$

(30)

where $\phi$ is the angle of the position of the source galaxy in the polar coordinate system, measured counterclockwise from West. Then we measure the average projected mass density in each radial bin $R$ (physical units) as

$$\Delta \Sigma(R) = \frac{\sum_i w_i \Sigma_{cr,i} e_+}{\sum_i (1 + m_i) w_i},$$

(31)

where $\Sigma_{cr}$ is the critical surface mass density for lensing, computed from the cluster redshift $z_c$ and the photometric redshift $z_{p,\text{best}}$ of the source galaxy. The index $i$ runs over source galaxies in the specified radial bin behind all foreground lensing clusters considered. We choose the weight $w_i$ as

$$w_i = \frac{w_g,i}{\Sigma_{cr,i}},$$

(32)

where $w_g$ is the weight factor of each source galaxy provided by the CFHTLenS shear catalogue. The critical surface density is introduced in the weight factor to downweight source galaxies whose redshifts are close to lens redshifts and therefore their weak lensing effects are inefficient (see, e.g., Mandelbaum et al. 2013).

One of the most important potential systematic effects in cluster weak lensing analysis is the dilution effect by cluster member galaxies (e.g., Medezinski et al. 2007; Okabe et al. 2013). One can mitigate the dilution effect by selecting appropriate background galaxies for weak lensing analysis. While photometric redshifts are available for individual source galaxies in the CFHTLenS catalogue, imperfect photometric redshifts lead to the contamination of cluster member galaxies in the source galaxy sample, even if the photometric redshift cut is applied to select only background galaxies. In this paper, we adopt the following procedure to construct a secure background galaxy sample. For each galaxy, the CFHTLenS shear catalogue provides the best photometric redshift estimate $z_{p,\text{best}}$ as well as the full probability distribution function (PDF) of the photometric redshift, $P(z_p)$. We then define a subsample of source background galaxies by

$$\int_{z_{p,\text{min}}}^{\infty} P(z_p)dz_p > p_{\text{cut}},$$

(33)

with $p_{\text{cut}} = 0.98$, and $z_{p,\text{best}} < 1.3$.

(34)

We adopt $z_{p,\text{min}}$ to be 0.05 higher than the upper limit of the cluster redshift bin of interest. The first condition assures that the PDF does not extend down to cluster redshifts, and therefore should be able to select background galaxies more securely than simple photometric redshift cuts based only on $z_{p,\text{best}}$. The second cut is included because photometric redshift estimates of galaxies with $z_{p,\text{best}} > 1.3$ are thought to be less secure (see, e.g., Kilbinger et al. 2013).
To test the validity of our approach to select the background galaxy sample, we check the average number density of background galaxies as a function of distance from cluster centres. We find that the average number density is nearly flat for low richness cluster samples, whereas the number density decreases toward the centre for high richness clusters, which can be explained by the lensing magnification as well as obscuration by cluster member galaxies. The lack of increase of the background galaxy number density toward the cluster centre assures that our background galaxy sample is not significantly contaminated by cluster member galaxies.

### 5.2 Model

We fit the stacked weak lensing signal with our theoretical model to extract cluster parameters. The mass distribution of individual clusters are assumed to follow the Navarro et al. (1997, hereafter NFW) density profile. We assume that the BCG selected in our algorithm to each cluster, but some BCGs defined in our algorithm may in fact correspond to satellite galaxies rather than galaxies in halo centres. We include this miscentring effect in the stacked weak lensing profile using the Fourier space approach developed by Oguri & Takada (2011). For the miscentring model, we adopt a two-component model that was also used by Oguri & Takada (2011). This model, with the explicit form presented in equation (29), assumes that one component is well centred and the other component whose offset PDF is described by the two-dimensional Gaussian distribution. Oguri & Takada (2011) found that the average convergence profile with the miscentring effect in the angular Fourier space is described by

\[
\kappa_{\text{NFW,off}}(\ell) = \kappa_{\text{NFW}}(\ell) \left[ f_{\text{cen}} + (1 - f_{\text{cen}}) \exp \left( -\frac{1}{2} \sigma_s^2 \ell^2 \right) \right],
\]

where \( f_{\text{cen}} \) is the fraction of the well-centred cluster component and \( \sigma_s = R_c/D_A(z) \) specifies the size of the offset PDF. Here we assumed \( R_{\text{cen}} \approx 0 \) in equation (29) for simplicity. For the original NFW profile in the Fourier space (see Oguri & Takada, 2011), in fact we employ the Fourier transform of a truncated NFW profile (Baltz, Marshall, & Oguri 2000), presented in Oguri & Hamana (2011), but choose the truncation radius sufficiently large to describe the truncated NFW profile.

The concentration parameter \( c_{\text{vir}} = r_{\text{vir}}/r_s \) is an important parameter that quantifies the mass concentration of the NFW profile. We assume the following mass and redshift dependences (Duffy et al. 2008)

\[
c_{\text{vir}} = c_{\text{norm}} \frac{7.85}{(1 + z)^{0.71}} \left( \frac{M_{\text{vir}}}{2 \times 10^{12} h^{-1} M_\odot} \right)^{-0.081},
\]

and treat the overall normalization \( c_{\text{norm}} \) as a parameter in order to take account of the uncertainty of the concentration parameter.

Given the Fourier space description of the NFW profile, the convergence and tangential shear profiles are computed as

\[
\kappa_{\text{off}}(R) = \int \frac{\ell d\ell}{2\pi} \kappa_{\text{NFW,off}}(\ell) J_0(\ell R/D_A(z)),
\]

where \( J_0(x) \) and \( J_2(x) \) are zero-th and second order Bessel functions. Since weak lensing in fact measures the reduced shear, we approximately compute the surface mass density for a fixed halo mass as

\[
\Delta \Sigma(R) = \frac{\Sigma_{\text{eff}}(\gamma_+ + \gamma_{\text{off}})(R)}{1 - \kappa_{\text{off}}(R)},
\]

where \( \Sigma_{\text{eff}} \) is computed using the mean lens and source redshifts of the sample.

### 5.3 Fitting procedure

We consider two redshift slices for the stacked weak lensing analysis, the low-redshift slice with \( 0.1 < z_{cl} < 0.3 \) and the high-redshift slice with \( 0.4 < z_{cl} < 0.6 \). We consider these two redshift bins given the possible change of cluster properties in our cluster sample at \( z \sim 0.35 \) (see, e.g., Figure 10). We set the photometric redshift cut (see equation 53) \( \tilde{z}_{p,\text{min}} = 0.35 \) and 0.65 for the low- and high-redshift cluster samples, respectively. For each redshift slice we consider four richness bins defined by \( 20 < N_{\text{cor}} < 25, 25 < N_{\text{cor}} < 35, 35 < N_{\text{cor}} < 50, \) and \( 50 < N_{\text{cor}} < 90 \). Thus there are 8 subsamples in total for the stacked weak lensing analysis. We only use clusters in the overlapping regions \( \sim 120 \text{ deg}^2 \) of SDSS DR8 and CFHTLenS.

The radial range of profile fitting must be chosen carefully to reduce various systematic errors. For instance, shear signals near the halo centre are difficult to interpret for several reasons. First, our calculation of reduced shear given in equation (40) involves an approximation which becomes less accurate toward the halo centre. Second, the dilution effect of cluster member galaxies is more pronounced near the centre, so any residual contamination of cluster member galaxies in the source shear catalogue, if exists, decreases tangential shear signals. Third, the CFHTLenS shear measurement is less tested again simulated galaxy images in the high shear regime like cluster centres. As shown in Becker & Kravtsov (2011) and Oguri & Hamana (2011), the maximum radius of fitting is also important for unbiased measurement, because of increasing contributions of the so-called two-halo term to the stacked weak lensing profile. Also stacking around random points suggests that there appears to be residual systematics in the CFHTLenS shear measurement at large radii. \( R \gtrsim 10 h^{-1} \text{ Mpc} \) (Miyatake et al. 2014; Covone et al. 2014). Thus we conservatively choose the radial range of our profile fitting to \( 0.158 < R/(h^{-1} \text{ Mpc}) < 2.09 \), which is divided into 7 logarithmically spaced bins with an interval of \( \Delta(\log R) = 0.16 \). For simplicity we do not consider the cosmic shear error, as the cosmic shear error is subdominant in the radius range considered here (see Miyatake et al. 2014).

Parameters of our shear profile model includes the halo mass \( \langle M_{\text{vir}} \rangle \), the normalization of the concentration parameter \( c_{\text{norm}} \), the fraction of the central component \( f_{\text{cen}} \), the miscentring size \( R_{\text{off}} \), the concentration parameter \( \Gamma_{\text{cen}} \), and the miscentring size \( R_{\text{off}} \). Since the miscentring parameters degenerate with the concentration parameter \( \Gamma_{\text{cen}} \), we add a conservative Gaussian prior to \( \log c_{\text{norm}} \) as \( \log c_{\text{norm}} = 0 \pm 0.2 \), and fix the miscentring size to \( 0.42h^{-1} \text{Mpc} \) based on the analysis result of the mock galaxy catalogue in Johnston et al. (2007). Therefore the number of degree of freedom of our fitting is 5.
The richness. To illustrate this point, we show the scaling mass inferred from stacked weak lensing correlates well with stacked weak lensing signals are detected significantly for all 8 cluster subsamples. As expected, the signals decrease as the mean halo mass, which are shifted vertically by -0.5, 0, 0.5, and 1 dex, respectively, for illustrative purpose. Solid lines show best-fitting NFW profiles including the miscentring effect (see Section 5.2 for more details).

Figure 18. Scaling relations between the mean richness ($\langle \tilde{N}_{\text{cor}} \rangle$) and the mean halo mass ($\langle M_{\text{vir}} \rangle$) inferred from the CFHTLenS stacked weak lensing analysis. Filled triangles show the relation for the low-redshift (0.1 < $z_{\text{cl}}$ < 0.3) cluster sample, whereas open squares show the relation for the high-redshift (0.4 < $z_{\text{cl}}$ < 0.6) cluster sample (see also Table 1). Solid lines with shading are power-law fits (equation 40) and 1σ error of the scaling relations.

5.4 Results

Stacked surface mass density profiles for low (0.1 < $z_{\text{cl}}$ < 0.3) and high (0.4 < $z_{\text{cl}}$ < 0.6) redshift cluster samples are shown in Figures 16 and 17, respectively. It is clear that stacked weak lensing signals are detected significantly for the 8 cluster subsamples. As expected, the signals decreases with increasing projected radius, which are found to be fitted reasonably well by our model including the miscentring effect (equation 39). From the comparisons with the theoretical model we derive constraints on model parameters such as the mean halo mass ($\langle M_{\text{vir}} \rangle$) and the fraction of the centred component $f_{\text{cen}}$. We summarize the results in Table 1.

The fitting results clearly indicate that the mean halo mass inferred from stacked weak lensing correlates well with the richness. To illustrate this point, we show the scaling relation in Figure 18. We do not find significant difference in the scaling relations between the low- and high-redshift clusters. Our result indicates that the richness limit of $N_{\text{cor}} > 20$ for the CAMIRA SDSS DR8 catalogue corresponds to the cluster virial mass limit of $M_{\text{vir}} \gtrsim 1 \times 10^{14} h^{-1} M_{\odot}$ over the redshift range of 0.1 < $z_{\text{cl}}$ < 0.6. The virial mass limit may be slightly lower at higher redshifts, possibly due to the increased scatter of the richness estimate as discussed above.

We quantify the mean mass-richness relations by fitting them to the following power-law relation

$$\log \left( \frac{\langle M_{\text{vir}} \rangle}{h^{-1} M_{\odot}} \right) = a_M \log \left( \frac{\langle \tilde{N}_{\text{cor}} \rangle}{30} \right) + b_M. \quad (40)$$

We find $a_M = 1.44 \pm 0.27$ and $b_M = 14.30 \pm 0.05$ for the low redshift cluster sample, and $a_M = 2.10 \pm 0.39$ and $b_M = 14.20 \pm 0.06$ for the high redshift cluster sample. The best-fit relations are shown in Figure 18.

In addition to the mean mass-richness relation, the stacked weak lensing analysis provides some insight into the halo miscentring effect. Although our constraints on the miscentring parameter $f_{\text{cen}}$ (see Table 1) is not tight due to the degeneracy with the concentration parameter, we see a trend that $f_{\text{cen}}$ is smaller at higher redshifts. In particular $f_{\text{cen}}$ is most significantly smaller than unity for high redshift, low-richness clusters. This is presumably due to the fact that these clusters intrinsically contain small number of cluster member galaxies, and therefore proper selections of central galaxies may be more challenging. Our result here is another example of how weak lensing can be used to study halo miscentring effects (Oguri et al. 2010, George et al. 2012, Ford et al. 2014). Finally we perform a simple test to compare the observed cluster abundance with the theoretical expectation. Specifically we adopt the power-law scaling relation obtained from the CFHTLenS stacked weak lensing analysis (equa-
Table 1. Results of stacked weak lensing analysis with the CFHTLenS shear catalogue.

| $N_{\text{cor}}$ range | $z_{\text{cl}}$ range | $N_{\text{cluster}}$ | $\langle N_{\text{cor}} \rangle$ | $\langle z_{\text{cl}} \rangle$ | $\langle z_{p,\text{best}} \rangle$ | $\log((M_{\text{vir}})/h^{-1}M_\odot)$ | $\log \epsilon_{\text{norm}}^a$ | $f_{\text{cen}}$ |
|------------------------|------------------------|----------------------|------------------|----------------|-----------------|-----------------|----------------|----------------|
| 20–25                  | 0.1–0.3                | 35                   | 22.3             | 0.25           | 0.86            | $14.04^{+0.11}_{-0.13}$ | $0.01^{+0.20}_{-0.19}$ | $0.77^{+0.23}_{-0.25}$ |
| 25–35                  | 0.1–0.3                | 29                   | 29.2             | 0.26           | 0.86            | $14.24^{+0.09}_{-0.13}$ | $-0.09^{+0.17}_{-0.16}$ | $0.83^{+0.17}_{-0.26}$ |
| 35–50                  | 0.1–0.3                | 14                   | 39.6             | 0.23           | 0.86            | $14.62^{+0.07}_{-0.09}$ | $-0.04^{+0.20}_{-0.18}$ | $0.49^{+0.24}_{-0.19}$ |
| 50–90                  | 0.1–0.3                | 4                    | 66.2             | 0.17           | 0.86            | $14.71^{+0.10}_{-0.10}$ | $-0.03^{+0.15}_{-0.11}$ | $0.99^{+0.61}_{-0.29}$ |
| 20–25                  | 0.4–0.6                | 291                  | 21.9             | 0.51           | 0.98            | $13.97^{+0.09}_{-0.11}$ | $0.04^{+0.17}_{-0.21}$ | $0.39^{+0.21}_{-0.12}$ |
| 25–35                  | 0.4–0.6                | 186                  | 28.8             | 0.51           | 0.98            | $14.12^{+0.10}_{-0.09}$ | $-0.04^{+0.18}_{-0.10}$ | $0.47^{+0.17}_{-0.20}$ |
| 35–50                  | 0.4–0.6                | 72                   | 40.3             | 0.50           | 0.98            | $14.40^{+0.10}_{-0.10}$ | $-0.04^{+0.20}_{-0.18}$ | $0.55^{+0.27}_{-0.20}$ |
| 50–90                  | 0.4–0.6                | 13                   | 55.2             | 0.52           | 0.98            | $14.85^{+0.11}_{-0.13}$ | $-0.03^{+0.20}_{-0.18}$ | $0.33^{+0.28}_{-0.18}$ |

$^a$ Note that the Gaussian prior $\log \epsilon_{\text{norm}} = 0 \pm 0.2$ is included in fitting.

Figure 19. The cumulative number distribution of clusters as a function of the corrected richness $N_{\text{cor}}$ for the entire SDSS DR8 footprint. Here we consider the cluster redshift range $0.1 < z_{\text{cl}} < 0.3$ where our richness estimates are more secure. The histogram shows the distribution in our CAMIRA cluster sample. The solid line shows the theoretical expectation from the mass-richness scaling relation of equation (40). The shaded region represents 1$\sigma$ range from the statistical uncertainty in the mass-richness scaling relation (see Figure 18).

In this paper, we have presented a new cluster finding algorithm, CAMIRA, which identifies the concentration of red-sequence galaxies in photometric surveys. The algorithm uses the SPS model to predict red-sequence galaxy colours for an arbitrary set of filters. The model must be calibrated using a sample of spectroscopic red-sequence galaxies in order to achieve enough accuracy necessary for various applications. For a given redshift we count the number of red-sequence galaxies at that redshift, where the “number” of individual galaxies is a smooth function of $\chi^2$ of fitting to the SPS model, using a spatial filter that is designed to subtract the background level. We also restrict the stellar mass range using a smooth filter function. We identify cluster candidates by locating peaks in the three-dimensional richness map, and each cluster candidate is refined by iteratively finding the BCG and best-fit cluster redshift. In addition the algorithm takes proper account of masking effects.

We have applied the algorithm to the SDSS DR8 imaging data covering $\sim 11960 \text{ deg}^2$. We have first calibrated the SPS model using a large sample of spectroscopic galaxies in SDSS and BOSS. We have constructed a catalogue containing 71743 clusters in the redshift range of $0 < z_{\text{cl}} < 0.6$ with the corrected richness $N_{\text{cor}} > 20$. The number of clusters per redshift bin increases with increasing cluster redshift, simply because the comoving volume increases. The comoving number density is roughly constant over the entire cluster redshift range.

We have compared the CAMIRA SDSS DR8 cluster catalogue with external cluster catalogues to test its performance. The comparison of our photometric cluster redshift estimates with spectroscopic cluster redshifts from the external catalogues indicates that the photometric cluster redshift is accurate with low bias and scatter. We have also compared the corrected richness with X-ray luminosities and temperatures and found good correlations. Scatters of these relations are comparable to those found in other optical SDSS cluster samples such as redMaPPer.

We have derived stacked weak lensing signals for the SDSS cluster catalogue using the public CFHTLenS shear catalogue. Despite the small overlapping area of $\sim 120 \text{ deg}^2$, to calibrate the mass-richness relation must also be taken into account for the cosmological analysis (More 2013).

6 SUMMARY

In this paper, we have presented a new cluster finding algorithm, CAMIRA, which identifies the concentration of red-sequence galaxies in photometric surveys. The algorithm makes use of the SPS model to predict red-sequence galaxy colours for an arbitrary set of filters. The model must be calibrated using a sample of spectroscopic red-sequence galaxies in order to achieve enough accuracy necessary for various applications. For a given redshift we count the number of red-sequence galaxies at that redshift, where the “number” of individual galaxies is a smooth function of $\chi^2$ of fitting to the SPS model, using a spatial filter that is designed to subtract the background level. We also restrict the stellar mass range using a smooth filter function. We identify cluster candidates by locating peaks in the three-dimensional richness map, and each cluster candidate is refined by iteratively finding the BCG and best-fit cluster redshift. In addition the algorithm takes proper account of masking effects.

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We have derived stacked weak lensing signals for the SDSS cluster catalogue using the public CFHTLenS shear catalogue. Despite the small overlapping area of $\sim 120 \text{ deg}^2$, to calibrate the mass-richness relation must also be taken into account for the cosmological analysis (More 2013).
we have detected stacked lensing signals significantly for all the 8 subsamples divided by redshift and richness. The mean halo mass inferred from the lensing analysis clearly correlates with richness. There is no significant difference of the mass-richness relations between low (0.1 < $z_{cl}$ < 0.3) and high (0.4 < $z_{cl}$ < 0.6) redshift cluster samples. The stacked weak lensing analysis indicates that the richness limit of about $M_{\text{vir}} \geq 1 \times 10^{14} h^{-1} M_{\odot}$. We have also obtained constraints on miscentring from the stacked weak lensing analysis. At the low redshift our results are consistent with no miscentring component ($f_{\text{cen}} = 1$), while miscentring appears to be significant for the high redshift clusters. The cluster abundance is found to be consistent with theoretical expectation obtained using the mass-richness relation calibrated by weak lensing, though for more careful comparisons we need to take account of the scatter of the mass-richness relation.

This cluster finding algorithm is developed with the application to ongoing and future wide-field optical imaging surveys (in particular Subaru Hyper Suprime-Cam; Miyazaki et al. [2012] in mind. In these future surveys, imaging data are much deeper than SDSS, allowing us to detect all the member galaxies of interest out to very high redshifts, $z \sim 1$. In addition we will be able to obtain better stacked weak lensing signals to examine the mass-richness relation more extensively. Furthermore, careful comparisons with cluster catalogs in other wavelength such as X-ray and SZ are important in understanding the mass-richness relation as well as miscentring effects. We can obtain independent information on the mass-richness relation from clustering analysis, such as the auto-correlation function and large-scale stacked weak lensing profile, which helps constrain the mass-richness relation further. These are necessary steps for turning cluster of galaxies into a useful probe of cosmology.

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Table A1. The CAMIRA SDSS DR8 cluster catalogue. The full table in the online edition only.

| RA (J2000) | Dec. (J2000) | zcl | N_{cor} | N_{mem} |
|-----------|-------------|-----|---------|---------|
| 0.000095  | 24.902249   | 0.4832 | 21.515 | 8.407   |
| 0.009577  | 5.288260    | 0.1761 | 29.235 | 29.164  |
| 0.012499  | 34.580621   | 0.3100 | 22.468 | 18.512  |
| 0.013423  | 22.861665   | 0.5140 | 21.928 | 7.573   |
| 0.013767  | 31.231751   | 0.4998 | 27.659 | 10.042  |
| 0.014742  | 31.785640   | 0.3100 | 22.468 | 18.512  |
| 0.016278  | 8.736973    | 0.4522 | 28.300 | 13.052  |
| 0.018126  | 7.216778    | 0.4409 | 21.166 | 10.407  |
| 0.025971  | −2.166898   | 0.5051 | 26.796 | 9.535   |
| 0.027360  | 21.655266   | 0.5380 | 26.743 | 8.559   |

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APPENDIX A: CAMIRA SDSS DR8 CLUSTER CATALOGUE

In Table A1 we provide a sample of the CAMIRA SDSS DR8 cluster catalogue. The full version of the table will be available in the online edition of the journal.