INTRODUCTION

Galaxy clusters are integral tools in our drive to test the \( \Lambda \)CDM cosmological model and our understanding of galaxy formation. The evolution of the cluster population with redshift for example, can impose important constraints on the matter density of the universe (Carlberg et al. 1996; Evrard 1997; Schuecker et al. 2003) and the growth of primordial density fluctuations (Frenk et al. 1990; White, Efstathiou & Frenk 1993; Fedeli, Moscardini & Matarrese 2009).

The deep potential wells of clusters offer a suite of laboratories within which detailed studies of gas-galaxy interactions are possible. There is evidence that clusters have been in place for a significant fraction of the star-forming history of the universe, meaning they can provide a unique insight into the how environmental effects shape the evolutionary path of galaxies.

There is therefore great merit in producing a homogeneous cluster census of the Universe, and much effort has gone into producing comprehensive cluster surveys. Efforts to this end are broadly separated into two wavelength domains: the optical–near-
Murphy et al.

IR and X-ray. We note in passing that cluster detection by SZ-decrement in the microwave is an emerging cluster survey technique that holds promise at high redshift (McInnes et al. 2009, Brodwin et al. 2010, Hincks et al. 2010, Vanderlinde et al. 2010).

X-ray detections exploit the hot intracluster gas accounting for the bulk of the cluster baryonic mass component (Cavaliere & Fusco-Femiano 1976; Allen, Schmidt & Fabian 2002). X-ray selected cluster catalogues tend to be robust to projection effects, probe large volumes and produce a cluster sample with well characterised masses. Cluster catalogues from large area X-ray surveys (e.g., Ebeling et al. 1999) identify bright, massive clusters, with their deep potential wells establishing the high electron densities required for strong X-ray emission. Whilst a cursory glance in the X-ray unveils the presence of high mass systems, to select those with lower masses, unresolved gas components, distant or gas-poor clusters, one must look to alternative approaches.

There has been a half-century history of cluster identification in the optical regime. Early ‘eyeball’ surveys of photographic plates produced the earliest cluster catalogues (Abell 1958; Zwicky, Herzog & Wild 1961; Abell, Corwin & Olowin 1989) and allowed the first statistical study of the cluster population. When cluster and group samples were later constructed with the help of digitised photographic plates (such as the APM; Dalton et al. 1992) and galaxy spectra (Eke et al. 2004), the task of identification passed from human to machine. With the advent of wide-field multi-band CCD imaging, assembly of vast galaxy samples has become the standard. For example, Sloan Digital Sky Survey (SDSS; York et al. 2000) optical imaging data has vastly increased both the volume and detail of detected astronomical sources, to date generating five-band $ugriz$ photometry for $\sim 230$ million objects (DR7, Abazajian et al. 2009). Although one can estimate galaxy redshifts photometrically based on SED template fitting (Csabai et al. 2003), neural networks (Collister & Lahav 2004) or a combination of the two (Abazajian et al. 2009 §4.6), photo-$cz$s are prone to large uncertainties and are generally unsuitable for accurate 3D reconstructions of the galaxy distribution (although for recent approaches using the entire photometric redshift distribution, see Liu et al. 2008). Armed with only the angular positions of galaxies, automated algorithms have been developed to identify clusters as projected overdensities in the plane of the sky (Lidman & Peterson 1996, Postman et al. 1996). These often come at the expense of model dependency and sensitivity to the boundaries and holes common in galaxy catalogues. More geometric approaches have made use of the Voronoi Tessellation (VT) to map the projected density distribution of galaxies. Using the Voronoi cell area as a proxy for the local galaxy density, VTs were first suggested as a non-parametric means of astrophysical source detection by Ebeling & Wiedemann (1993), and later cluster detection in Ramella et al. (2001). Voronoi techniques have also been used in void detection ( Ryder et al. 1995; El-Ad, Piran & da Costa 1996) and the identification of large scale structure (Icke & van de Weygaert 1991). However, these approaches tend to suffer from contamination arising from the inclusion of background and foreground field galaxies.

Gladders & Yee (2000) proposed a powerful method that picks out the near ubiquitous signature of galaxy clusters from photometric surveys. Star formation rates of galaxies bound in the potential wells of clusters are suppressed when the cold gas supply is depleted by environmentally-driven stripping or starvation processes (Balogh, Navarro & Morris 2000). The passively evolving stellar populations in these galaxies develop strong metal absorption lines blueward of 4000Å giving rise to a break, or step, in their spectra. In broad-band photometric filters, these cluster members appear nearly uniformly red between the bands that straddle the spectral break. Because cluster galaxies occupy a wide range of masses (luminosities) these characteristic colours produce a distinct ridge-line, or “red sequence” (Bower, Lucey & Ellis 1992) in colour-magnitude space. The dichotomy between this quiescent population of predominantly E/S0 galaxies and the star-forming population of spiral-dominated field galaxies is observed as a bi-modality of galaxy colours. With increasing redshift, the 4000Å break moves redward; the Gladders & Yee (2000) prescription for cluster detection exploits both the strong colour bi-modality in the galaxy distribution, and the colour-redshift relation to isolate clusters of galaxies over a range of epochs.

With a growing body of infrared data (specifically, the IRAC cameras on-board the Spitzer Space Telescope), efforts such as the Spitzer Adaptation of the Red-Sequence Cluster Survey (SpARCS, Wilson et al. 2009) have already turned to pushing red-sequence cluster searches beyond the optical/NIR regime. With evidence of cluster sequences in place up to $z \sim 1.5$ (Papovich et al. 2010, Havasi et al. 2011) and perhaps as early as $z = 3$ (Kodama et al. 2007, Doherty et al. 2010), tracking the 4000Å break further redward shows great potential in filling the 1.4 $< z < 2.2$ cluster desert. These distant systems may potentially hold some crucial clues for our understanding of galaxy formation and evolution.

Future observational campaigns such as the Large Synoptic Survey Telescope (LSST, Ivezić et al. 2008) are set to push forward the frontiers of wide-area, deep multi-band optical sky surveys. More immediately Pan-STARRS-1 (PS1; Kaiser et al. 2002), the first of four 1.8m telescopes, is currently imaging 3/4 of the sky with deep, well characterised (Stubbs et al. 2010) five-band photometry. Algorithms capable of processing the petabyte-scale sky surveys of these next-generation facilities will be best placed to supply data products fully exploiting their advances. Cluster selection by red sequence is set to remain highly relevant to the construction of cluster catalogues using these forthcoming surveys.

One approach to cluster detection in these deeper datasets is through “matched-filter” (MF; Postman et al. 1996) algorithms that distill the large body of collected cluster data into a likelihood function, recovering systems by maximising the likelihood of survey data fitting the model. In particular, these filters may specify the cluster luminosity function, radial density distribution, behaviour of the red sequence ridgeline and in some cases the presence of a central Brightest Cluster Galaxy (BCG) (maxBCG, Koester et al. 2007b). MF algorithms often confer redshift and richness estimates as part of the detection procedure. The MF technique has been successful in extracting cluster signals from a diverse range of galaxy surveys, including the SDSS (goto et al. 2002, Koester et al. 2007a) and Canada France Hawaii Telescope Legacy Survey (CFHTLS, Gladders & Yee 2005, Thanjavur, Willis & Crampin 2009). The maxBCG SDSS cluster catalogue (Koester et al. 2007a) has facilitated a more detailed study of the cluster red sequence (Hao et al. 2009), which may in turn provide added refinements to future algorithms.

However, the advantage of MF algorithms can also be their drawback: such techniques will preferentially recover the clusters they are designed to match, but those not fitting the model are less likely to be identified. Many matched filter approaches also are based on uniform background galaxy distributions, and experience a degraded performance (Kim et al. 2002) under more realistic backgrounds.

1 http://pan-starrs.ifa.hawaii.edu
Our cluster detection philosophy is designed to be distinct from, but entirely complementary to the variety of matched filter algorithms available. This study relaxes theoretically and observationally-motivated constraints, permitting a broader exploration of systems with projected overdensities. Specifically, we do not assume cluster red sequences occupy a particular position in colour-magnitude space, nor do we stipulate preferred distributions for the projected position of cluster members on the sky. Through this approach we hope to provide both an independent catalogue of clusters and a means to refine our understanding of characteristic cluster properties. The lack of selection criteria in our algorithm permits a double-check of the detections, since we can ask if the identified system conforms to our expectations. As we shall later demonstrate (see §5 and Figure 17), the prescription presented here may lead to improved recovery of certain systems and better agreement with X-ray cluster data. Moreover, because our proposed technique makes only two assumptions about cluster properties, it is sensitive to a wide range of clusters, including aspherical/asymmetric systems in the process of merging (Clowe et al. 2006) and fossil groups (Schirmer et al. 2010) with luminosity functions unlike a Schechter (1976) function.

In this paper, we present our detection prescription, which involves a blind scan of colour-magnitude space (to locate cluster sequences) and a Voronoi tessellation technique (to estimate the galaxy surface density distribution). Requiring only two bands to detect spectral breaks, our approach provides a very efficient method of detecting clusters in wide-area CCD imaging of the sky. Whilst algorithms have in the past used Voronoi tessellations to find clusters, previous attempts either do not exploit the red sequence or instead use photometric redshift distribution functions that rely sensitively on the absolute calibration and number of photometric bands (van Breukelen & Clewley 2009; Soares-Santos et al. 2011). Instead, we apply the algorithm and test it on a 7 square degree sample of SDSS Stripe 82 data. A companion paper (GMB11) presents the full Stripe 82 catalogue covering the full 270 square degrees.

The outline of this paper is as follows. In section 2 we define the data used for the cluster search in the SDSS and mock catalogues. Section 3 describes the algorithm step-by-step. Section 4 describes the application and testing of the algorithm using real astronomical data, followed by a brief comparison with existing cluster catalogues in section 5. We describe the detection of mock clusters in simulated data in section 6, followed by performance tests on the simulated catalogues. In section 7 we summarise our findings.

Throughout, we assume a ΛCDM cosmology with Ω_m = 0.3, Ω_Λ = 0.7, H_0 = 70 km s^{-1} Mpc^{-1} and h = H_0/100 km s^{-1} Mpc^{-1}. For SDSS data we use the Sloan photometric system (Gunn et al. 1998) and “model” magnitudes.

2 DATA

2.1 SDSS Stripe 82

We extract Sloan Digital Sky Survey Data Release 7 griz photometry for all sources with extinction-corrected (Schlegel, Finkbeiner & Davis 1998) r-band model magnitudes r \leq 24 in the deep coadd stripe centred on the celestial equator (“Stripe 82”) from the SDSS Catalog Archive Server (CAS). To minimise stellar contamination, we select only galaxies where the offset between the r-band PSF and model magnitudes satisfies |r_{PSF} - r_{model}| > 0.05. We exclude bright (r_{model} < 14) galaxies and spurious sources such as overly de-blended galaxies and fragmented stellar haloes.

Although no spectroscopic or photometric redshift estimates are used in detections, we post-process the cluster catalogue to estimate the redshift of each system. Cluster galaxies are assigned spectroscopic redshifts by matching source positions in the SDSS DR7, WiggleZ DR1 (Drinkwater et al. 2010) and 2SLAQ (Croom et al. 2009) catalogues to within 1". Where spectroscopic redshift data is unavailable, we use SDSS DR7 photometric redshifts (see Abazajian et al. 2009 and references therein). To increase both the source catalogue redshift completeness and the redshift accuracy for galaxies with no spectra, we supplement these data with additional photometric redshifts. We select all galaxies later identified by ORCA in the GMB11 Stripe 82 catalogue and estimate their redshifts using the hyperz code\footnote{http://webast.ast.obs-mip.fr/hyperz} (Bolzonella, Miralles & Pello 2000) with ugri model magnitudes and errors. The SDSS Stripe 82 input catalogue contains 11,358,087 galaxies with Galactic extinction-corrected (Schlegel, Finkbeiner, & Davis 1998) griz model magnitudes, over \(-50^\circ < \alpha < 50^\circ\) and \(\delta = \pm 1.25^\circ\). In this study, we concentrate on a 7 square degree sub-region within this catalogue, centred at \((\alpha, \delta) = (355.52^\circ, 0^\circ)\) comprising 291,389 galaxies (magnitude cuts applied to these galaxies for cluster detection are discussed in §3.7.1). This sample, covering the same area as the mock survey described below, was considered a large enough observational dataset with which to test the algorithm. GMB11 describe findings from the ORCA catalogue based on the full 270 square degree dataset.

2.2 Mock Pan-STARRS Medium Deep Survey catalogue

Cai et al. (2009) discuss the assembly of a light cone from the Millennium Simulation (Springel et al. 2005) with a 3° opening angle, equivalent to a single pointing of the Pan-STARRS Telescope 1 (PS-1), and the area of a single MDS tile. The Millennium Simulation provides the ΛCDM architecture into which galaxies are populated using the Bower et al. (2006) semi analytic GALFORM model (Cole et al. 2000). This creates a dataset with PS-1 griz photometry for 2,346,468 galaxies down to a magnitude limit of r < 27.5 (equivalent to the expected 5σ depth for the PS-1 MDS) and a median redshift of \(z = 1.05\). The similarity of the PS1 bands to the SDSS photometric system allows us to apply the same magnitude limits as those set for the Stripe 82 data (§3.7.1).

3 THE METHOD

In this section we first outline, and then detail the main components of the ORCA cluster detector.

3.1 Algorithm Outline

Here we describe the main steps of the ORCA algorithm. With photometry in several bands, we calculate galaxy colours in consecutive \((g-r, r-i, \text{etc.})\) band pairs.

1 We define a simple photometric selection using the colours and magnitudes of the sample. This selection could be simple, for example a narrow slice(s) in colour-magnitude space(s), or a more
Figure 1. A depiction of the ORCA detector applied to a 9’x9’ cut-out region of Stripe 82. Starting with all galaxies in the box (first panel), a photometric selection (2) isolates galaxies within a specific redshift range (second panel); any clusters in this field will be evident as surface overdensities. In the third panel, we compute the Voronoi diagram (3.4) of the distribution to estimate the surface density of remaining galaxies. These are separated into overdense (yellow) and underdense (grey) cells in panel four, according to how likely they are to belong to a random distribution (3.4). In the final panel, we use a Friends-Of-Friends percolation algorithm (3.5) to connect overdense cells until the density of the whole system falls below a density threshold. Galaxies in the blue cells become members of a cluster if there are at least \( N_{\text{min}} \) linked members.

3.2 Photometric filtering

In large-scale imaging surveys, groups and clusters are apparent as overdensities in the projected distribution of galaxies. Cluster detection methods reliant only on determining the projected galaxy density distribution are often plagued by two problems: (i) projection effects contaminating clusters with unassociated foreground and background galaxies (ii) the inclusion of spurious cluster detections arising from noisy data or chance projected overdensities.

To mitigate these problems, the contrast of genuine clusters can be enhanced by applying a photometric selection filter in colour-magnitude space, to isolate the red-sequence ridge-line. We parametrise our selection as a slice in colour-magnitude space, to isolate the red-sequence ridge-line. This selection function can be modified in successive applications of the algorithm to blindly scan the full photometric space, and thus isolate red-sequences across a range of redshifts (Gladders & Yee 2000, 2005).

2 In each pass of the algorithm, we apply the photometric selection to the catalogue, thus greatly restricting the total number of galaxies under consideration. In the case of using two colours concurrently, this can be a very effective means of reducing foreground contamination of a putative cluster characterised by some red-sequence.

3 After the selection, we calculate the Voronoi diagram of the projected distribution of galaxies on the sky. The inverse of the area of each convex hull surrounding each galaxy can be used as an estimate of the local surface density.

4 Galaxies residing in dense cells (satisfying some threshold criteria) can be connected together into conglomerations. If enough galaxies are joined together in this way, we define a cluster.

5 In the blind scan, successive photometric cuts may select the same structures (since the adjustment of the selection is by design less than the typical width of a red-sequence). Multiple detections of the same structure are identified and reduced to a single detection (we discuss how this was implemented in §3.6).

An illustrative overview of the above procedure can be seen in Figure 1.

Figure 2. The redshift evolution of the observed-frame r-i colour from a sample of mock galaxies. The colours indicate the density of galaxies at each point, with red being the highest. We are able to exploit this observed relation to isolate cluster galaxies within a specific redshift range by using a selection (such as the shaded strip in this Figure) to select galaxies from a narrow colour range.

3.2 Photometric filtering

In large-scale imaging surveys, groups and clusters are apparent as overdensities in the projected distribution of galaxies. Cluster detection methods reliant only on determining the projected galaxy density distribution are often plagued by two problems: (i) projection effects contaminating clusters with unassociated foreground and background galaxies (ii) the inclusion of spurious cluster detections arising from noisy data or chance projected overdensities.

To mitigate these problems, the contrast of genuine clusters can be enhanced by applying a photometric selection filter in colour-magnitude space, to isolate the red-sequence ridge-line. We parametrise our selection as a slice in colour-magnitude space, defined by a colour-magnitude normalisation (\( c_{\text{m20}} \), the colour at twentieth magnitude), slope \( \beta(c_{\text{m20}}) \) and width \( \sigma(c_{\text{m20}}) \). The expected evolution of red sequence colours is constrained from simple stellar evolution models, meaning scans over an appropriate set of photometric selection filters allows the isolation of clusters over a slew of redshifts. Figure 2 shows the redshift evolution of galaxy colours in a sample of mock galaxies from Merson et al. (2011, in preparation) and shows an additional advantage in using such filters. The two tracks visibly demonstrate the bimodality in galaxy colour that manifests itself as the “red sequence” (lower track, Bower, Lucey & Ellis 1992) and “blue cloud” (upper track). By selecting galaxies within specific colour range \( \Delta c \) (as denoted by the green region in the Figure), one may isolate red sequence cluster galaxies within the redshift range \( \Delta z \). Contaminants in this selection are bluer galaxies from higher redshifts. By simultaneously selecting galaxies from two photometric selections in different colours, one can eliminate degeneracies between colour tracks. We discuss this further in the following section.

The algorithm allows \( \beta(c_{\text{m20}}) \) and \( \sigma(c_{\text{m20}}) \) to adopt any values as the detector scans through colour-magnitude space. The simple prescription we adopt is that of a fixed slope and width with normalisation. Although the observed-frame sequence slope is known to evolve with redshift (Gladders & Yee 1998, Stanford, Eisenhardt & Dickinson 1998, Stott et al. 2009), our choice of photometric selection width encompasses a range of sequence gradients large
enough to account for evolution as the algorithm searches to deeper redshifts. Analysis of mock clusters from the Millennium Simulation suggests this approach probes at least 2.5(1.5) magnitudes fainter (brighter) than the observed characteristic galaxy flux at the redshifts clusters are detected in this study. With measurements from a large ORCA cluster catalogue, further refinements to the algorithm may include a description of how the sequence slope varies with normalisation cm20. The values adopted for β and σ are discussed in §3.7.

We scan through colour-magnitude space in a colour CA from blue to red, placing down a series of M photometric selection filters f(CA1), f(CA2)…f(CAM) by increasing the normalisation cm20 in small increments dc. The size of this increment, set in §3.7.1 allows adjacent filters to overlap, ensuring clusters close to the boundary of a filter are well sampled. Because each photometric selection isolates cluster galaxies (where they exist) from a specific redshift range, the detector can identify multiple clusters in the same line of sight. We determine the sensitivity of the algorithm to projection in §4.6.4.

3.3 Dual-colour photometric filtering

Although only one colour is necessary to detect clusters, Figure 2 notes the colour-redshift degeneracy apparent in attempting to isolate a redshift regime from a single colour selection. One can break the degeneracy and further reduce the field galaxy contamination by identifying the colour range cluster members have in a second colour CB, and subsequently applying a series of joint photometric filters in both CA and CB. To establish the CB colour range to scan, we take all cluster members from the preliminary detection (CA only), de-trend their sequence slopes and fit a Gaussian to the colour distribution. The CB colour range ∆CB is taken to be ±1σ from the Gaussian mean.

If the Gaussian fit is poor, detection of a clear sequence in both CB and CA is less likely. In this case ∆CB is simply ±1σ from the median of the CB colour distribution. The algorithm then scans over this second colour range and attempts to detect the cluster in both colours.

A filter pair in CA and CB (hereafter {CA, CB}) requires a detectable sequence in both colours, and amplifies the cluster signal by eliminating field galaxies in the CA filter that fail to appear within the CB filter. Any cluster in the final catalogue detected in CA must therefore also have been detected in CB. This improves the robustness of the algorithm and the reduction of contaminants from spurious detections. Because sub-filters overlap in CB colour-magnitude space, the same cluster may be detected in multiple filters. We apply the prescription described in §3.7.1 to identify and merge clusters that have been detected in more than one filter. The number of selection filters used to sample any colour range depends on the sampling interval dc set in §3.7.1

3.4 Identifying overdensities with the Voronoi tessellation

After increasing a cluster’s detectability by suppressing field galaxies with photometric filters, the next step is to calculate the local surface density of each galaxy. Galaxies residing in common regions of enhanced density can then be grouped together into clusters. To quantify the surface density field, we divide the galaxies into Voronoi cells using qhull 4 (Barber, Dobkin & Huhdanpaa 1996). The Voronoi diagram is a tessellation of convex hulls, or cells, with each galaxy occupying only one cell. All positions inside a given cell are closer to the cell’s nucleus (the galaxy) than any other. Unlike many other detection techniques, the Voronoi Tessellation (for VT cluster detection, see Ebeling & Wiedemann 1993; Ramella et al. 2001) does not smooth the data, is robust to cluster ellipticity (Plionis, Barrow & Frenk 1991) and can be applied to a variety of survey geometries. VTs do not suffer from spurious detections around survey boundaries and edges, and are thus well suited to analysing astronomical data with localised camera defects, excised bright stars and other sources of incompleteness. The left and middle panels of Figure 3 respectively show the Voronoi diagrams for a random point distribution and galaxies with identical mean densities Σ. Galaxies in more concentrated regions tend to have smaller cells.

We define the reciprocal of the galaxy cell area (a) as an estimate of the galaxy’s local surface density Σg. Searching for connected regions of high density identifies statistically significant structures. To determine if a galaxy resides in a high density region of the survey, we evaluate the statistical significance of finding a

---

4 http://www.qhull.org
cell of area $a_{\text{g}}$ in a random field with mean cell area $\bar{a}_{\text{R}}$. We use the Kiang (1966) cumulative function for a Poissonian distribution of points:

$$P(a) = \int_0^a dp = 1 - e^{-4a} \left( \frac{32a^3}{3} + 8a^2 + 4a + 1 \right) \quad (1)$$

where $a = (a_{\text{g}}/\bar{a}_{\text{R}})$. The right panel of Figure 2 shows the distribution $P(a)$ for cells in an example galaxy field relative to a Poisson distribution of the same field size and number of points. Candidate cluster galaxies residing in overdense regions can be selected by cell areas statistically unlikely to arise in a random distribution. An excess of galaxy cells is apparent for low $P(a)$ compared to the random distribution. We identify all galaxies with $P(a_{\text{g}}) < P_{\text{thresh}}$ in order to select a population of clustered galaxies. The choice of overdensity probability threshold is discussed in \[3.7.2\].

### 3.6 Producing a cluster catalogue

In §3.2 and §3.3, we noted that adjacent photometric filters applied to the input catalogue overlap in colour-magnitude space. With this sampling strategy, the same cluster could be detected in multiple filters. Figure 4 shows a sequence of Voronoi tessellations applied to the same area of sky under photometric filters sensitive to different redshift ranges. Because colour scans sample the colour range of a red-sequence at a specific redshift, the cluster will be detected in multiple scans (with a peak contrast where the selection is most effective). In cases of clusters detected multiple times in different photometric filters, the “best” cluster is identified and added to the final cluster catalogue.

For two candidates to be considered detections of the same system, they must have sufficiently similar spatial positions, red sequence fits and cluster members. We quantify the similarity in cluster sequences using linear fits to the colour-magnitude relation for the galaxies in each cluster detected. Sequence slopes can in principle adopt any value permitted by the width of the photometric filter (defined here as $\sigma_f$) it was selected in. We quantify the similarity between two sequences with the following criteria:

- **Sequence match 1 ($\Delta S_1$):** True if the sequence separation is $< 0.5\sigma_f$ in colour for at least 25% of the magnitude range $m_{\text{BCG}} - m_{\text{BCG}} + 5$.
- **Sequence match 2 ($\Delta S_2$):** True if the sequence separation is $< \sigma_f$ in colour difference for at least 50% of the range described in $\Delta S_1$.
- **Sequence match 3 ($\Delta S_3$):** True if the colour difference at 20th magnitude, $(\Delta m_{\text{core}})$ between the two sequences is $< \sigma_f$.
- **Sequence match 4 ($\Delta S_4$):** True if the clusters were detected in adjacent (overlapping) filters.

To define the similarity in cluster membership, spatial position and extent, we describe the common-galaxy fraction and projection extent for two clusters, CL$_1$ and CL$_2$:

- **Common galaxies (cg$_{1,2}$):** the fraction of galaxies in CL$_1$ that also belong to CL$_2$. Similarly, cg$_{2,1}$ is the fraction of CL$_2$ galaxies also appearing in CL$_1$. The BCG$_{id}$ boolean notes when clusters share the same BCG.
- **Projection extent (pe$_{1,2}$):** the fraction of galaxies in CL$_1$ that lie within the Voronoi cell boundaries of the CL$_2$ cluster. As with cg, pe$_{2,1}$ is the case for CL$_2$.

With these measures, five tests of “cluster similarity” were devised (Table 1). A pair of clusters must pass at least one to be considered detections of the same system. Each of these tests account both for the spatial and colour characteristics of the clusters. Because no merging can proceed purely by colour similarity or spatial coincidence, this ensures the separation of associated but distinct systems, and clusters in projection. We balance these requirements with the need to prevent multiple instances of the same cluster appearing in the final catalogue. Where matches between two clusters exist, the thresholds in Table 1 make it likely the two systems will be merged.

To define the “best” cluster from a list of candidates, we pick out the system with the largest reduced flux - the total flux (in the detected band) of all but the three brightest cluster members. This
Figure 5. (Top) Colour-magnitude diagrams for the 126 Abell 2631 members selected in this study. The yellow dot notes the position of the cluster r-band brightest cluster galaxy. The black lines denote photometric selection filter fits to the data and indicate the slope (β), normalisation (solid, c_{m20}) and width (dashed, σ). The identified members are split into those inside (blue) and outside (red) the 3-sigma cut used to estimate the filter width. Grey data indicate all galaxies that were not identified as members of the cluster out to a radius of 7-arcminutes from the cluster centre. The red dashed line in the g-r colour indicates the blue limit imposed by the Virgo cluster, and the equivalent lines in r-i and i-z denote the lowest c_{m20} identified from cluster sequences in our search of the 7 square degree Stripe 82 survey. (Bottom) The colour-magnitude diagrams for galaxies in a region of the same area located in a field environment.

Table 1. The set of conditions used to consider whether two clusters are multiple detections of the same system. If any one of these conditions are satisfied, the algorithm picks the “best” cluster of the two.

| # | Constraint |
|---|------------|
| 1 | (c_{g1,2} OR c_{g2,1}) > 0.5 |
| 2 | (pe_{1,2} OR pe_{2,1}) > 0 AND ΔS_1 |
| 3 | BCG_{id} AND ΔS_2 |
| 4 | (pe_{1,2} OR pe_{2,1}) > 0.8 AND ΔS_3 |
| 5 | (pe_{1,2} OR pe_{2,1}) > 0.8 AND ΔS_4 |

3.7 Algorithm parameters

This section defines the values adopted for the algorithm parameters described in §3.2-§3.5.

3.7.1 Photometric filtering

In both mock and real datasets, we limit our search for clusters to three colours: g-r, r-i and i-z. These are used to form joint selection filters combining two colours: {g-r, r-i} and {r-i, i-z}.

Each photometric filter is described by a colour normalisation c_{m20}, slope β(c_{m20}) and width σ(c_{m20}). For this study and that of GMB11 we demonstrate the detector with an unchanging filter slope and width. In order to set β and σ for each colour, 126 members of Abell 2631 (Abell, Corwin & Olowin 1989) are visually identified in an i, r and g composite Stripe 82 image. At redshift z = 0.278 (Bohringer et al. 2000), this system is the richest Abell cluster in Stripe 82 and shows evidence of a clear sequence in all three colours used in this study.

A linear fit to the colour-magnitude sequence was applied to determine β for each colour. The filter widths were set using a method akin to that described in Gladders et al. (1998); we first remove the slope in each sequence and then exclude 3σ outliers. Starting at the line fitted to the cluster sequence, we increase the width in equal amounts above and below this line until we enclose 90% of the remaining members. We define this as the filter width σ for that colour.

Figure 5 shows the colour-magnitude sequence of the identified members in the three colours (top) compared to a field of the
same area with no cluster present (bottom). Blue (red) points identify members that were inside (outside) the $3\sigma$ cut used to identify outliers. Grey data correspond to galaxies that were within $7'$ of the cluster centre and not picked as cluster members. Table 2 lists the fitted filter parameters for each colour (corresponding to the black lines in Figure 5) in addition to the colour range and number of filters used in our cluster search. Following our decision in §3.2 to use a fixed slope, we adopt the largest filter width ($\sigma_f = 0.152$) for all colours, and use this to define the input galaxy magnitude limit for each band. Magnitude limits are applied to reduce the number of input galaxies with high levels of photometric uncertainty. We set these as the faintest magnitude where the photometric uncertainties fall below 0.68\(\sigma_f\).

We set limits for each band based on a sample of 100,000 galaxies from Stripe 82. Figure 6 shows the galaxy photometric error distribution for the $r$-band, and from this we set a magnitude limit of $r \leq 23.5$. This is slightly more conservative than the limit implied by the error distribution ($r \leq 23.8$) because we aim to include only sources with good photometry. The magnitude limits applied are 24.0, 23.5, 23.3, 21.6 in the $g$, $r$, $i$ and $z$ bands respectively, resulting in a source catalogue of 69,797 galaxies. With the added depth from Stripe 82 photometry, these limits permit an exploration of the red sequence to at least 2.5, 3 and 1.5 magnitudes respectively for the $g$, $r$, $i$, and $z$ bands, respectively on the probability threshold $P_{\text{thresh}}$. Under this prescription, higher-signal cluster members are detected with high levels of confidence, while lower-signal members are classified as unclustered at the probability threshold $P_{\text{thresh}}=0.048$.

Figure 6 shows the galaxy photometric error distribution for the $r$-band, and from this we set a magnitude limit where at least 50% ($0.68\sigma$) of the faintest galaxies remain in a colour slice of width $\sigma_f = 0.152$. Whilst the data suggest a limit of $r \leq 23.8$, we opt for a slightly more conservative $r \leq 23.5$ limit (red vertical dashed line).

The bluest filter pair we employ is $g-r$. To prevent the detection of spurious systems bluer than the $z = 0$ red-sequence in this colour we determine a blue limit by extrapolating the colour-magnitude relation (CMR) for Coma (Smith et al. 2009) and Virgo (Rines & Geller 2008) to $r = 20$. The $c_{\text{mag20}}$ normalisation for Coma (Virgo) was estimated as 0.6 (0.47); we use the latter as the bluest filter possible in the $g-r$ colour. We do not apply similar limits to the other colours, but the normalisation below which no sequences were detected in $r-i$ and $i-z$ is described in §4.1. Figure 5 shows these limits as red dashed lines.

Finally, the detection algorithm uses photometric filters that overlap in colour-magnitude space, preventing clusters close to filter edges from being poorly sampled. A sampling interval in colour space of $dc = 0.04$ is chosen, corresponding to an overlap of approximately 75% between adjacent filters based on $\sigma_f$, the filter width.

3.7.2 Voronoi Tessellation and connection of overdense regions

The initial identification of clusters in projected high density regions and the subsequent percolation of their members depends respectively on the probability threshold $P_{\text{thresh}}$, and the critical density $\Sigma_{\text{crit}}$. We parametrise the critical density $\Sigma_{\text{crit}}$ as a scalar multiple of $\Sigma$ such that both detection parameters have a mean density dependence. In the left-hand sequence of Figure 7 we note the effect a range of $(P_{\text{thresh}}, \Sigma_{\text{crit}})$ combinations have on the recovery of Abell 2631 within a box of scale 13.6'. By tracking the detector’s assignment of Voronoi cells to cluster and field, we compare members visually identified to the recovery of this cluster under different parameter combinations. The cells are colour-coding into four groups to differentiate detected and visually identified members. Grey cells show galaxies neither detected nor identified as cluster members. Green cells denote detected members that were also visually identified, orange for where the detector did not assign cluster membership despite our classification as such from the imaging, finally red cells are detected members not visually identified as members. We stress the latter group in no way indicates the purity of the cluster, as we are both incomplete and subjective in our identification of genuine cluster members. However, this exercise does provide a useful indication of detector performance when compared to our visual impression of cluster membership.

The detection grids show re-detection is broadly insensitive to the range of parameters explored. At higher probability thresholds (increasing row number) the cluster expands to form a more extended structure. This growth is moderated by the introduction of a minimum cell density. We exclude $\Sigma_{\text{crit}} = 20 \Sigma$ as it removes a significant fraction of visually identified members on the periphery of the cluster. The middle ground between detecting a more compact system ($P_{\text{thresh}}=0.005$) and potentially increasing the interloper fraction ($P_{\text{thresh}}=0.015$) suggests the balance of detection completeness and cluster purity lies with $P_{\text{thresh}}=0.01$. We note from Figure 3 there are at minimum twice as many clustered cells as unclustered at $P(a) \leq 0.01$. Although $(0.01,0.01 \Sigma)$ and $(0.01,0.1 \Sigma)$ appear identical in their recovery of the cluster, we require a non-zero density constraint to filter out spurious low

Table 2. Filter parameters fitted from Abell 2631, the ranges searched and the number of filters in each colour. The blue limit in $g-r$ corresponds to an extrapolation of the Virgo CMR, whilst the others permit a full sweep of the available data. The emboldened figure is the largest filter width ($\sigma_f$), and is adopted for all colours.

| Colour | Slope (β) | Width (σ) | Range | Filters |
|--------|-----------|-----------|-------|---------|
| $g-r$  | −0.048    | 0.152     | 0.47~2.00 | 39 |
| $r-i$  | −0.017    | 0.067     | 0.00~1.22 | 38 |
| $i-z$  | −0.023    | 0.110     | −0.10~1.10 | 31 |

Figure 6. The SDSS model $r$-band photometric error in a sample of 100,000 Stripe 82 galaxies. These data are used to set a magnitude limit where at least 50% ($0.68\sigma$, black horizontal dotted line) of the faintest galaxies remain in a colour slice of width $\sigma_f = 0.152$. Whilst the data suggest a limit of $r \leq 23.8$, we opt for a slightly more conservative $r \leq 23.5$ limit (red vertical dashed line).
Figure 7. Effect of detection parameters on Abell 2631 (left, box scale 13.6' × 13.6') and a compact group (right, box scale 3.5' × 3.5'). Colour key: Grey are cells with field galaxies, green are galaxies identified by the algorithm that were also visually identified as members. Red cells are members assigned to the cluster by the detector but not visually identified as cluster members. Orange cells are galaxies that failed to be correctly identified by the algorithm as cluster galaxies, but were defined as such visually. The circle around Abell 2631 corresponds to a $1\, h^{-1}\text{Mpc}$ radius at the cluster redshift.

amplitude systems and prevent large clusters from percolating into giant connected structures. We consequently adopt the parameter combination $(P_{\text{thresh}}, \Sigma_{\text{crit}})=(0.01,10\bar{\Sigma})$. To ensure these parameters are not biased to the detection of high mass systems, we use 11 members of a visually identified compact group to perform a re-detection in the same parameter ranges. The right-hand sequence in Figure 7 with boxes of scale 3.5', shows the recovery of this group, and indicates group scale detection is robust to the range of parameters explored. The trade-off between completeness and purity is similarly evident here, with $(0.01,10\bar{\Sigma})$ remaining a good compromise between the two.

In both cases (and more generally) there is a tendency to underestimate the total number of cluster members. This arises from an inevitable feature of Voronoi Diagrams implying the algorithm is unlikely to recover all cluster members. The suppression of the field galaxy population with photometric filters causes an abrupt drop in galaxy surface density at the cluster boundary. Because the Voronoi cells of peripheral members have a limited number of field galaxies to constrain their boundaries they adopt larger areas. Such cells may then be rejected as members because their areas are inconsistent with that population. Nevertheless, tests with mock catalogues allow us to quantify the impact this effect has on the cluster purity, as discussed later in §6.

4 SDSS EQUATORIAL STRIPE 82 CLUSTER CATALOGUE

4.1 The catalogue

We applied the detector to a 7 square degree sample of Stripe 82, using the limits described in §2 and parameters described in §3.7. Here we describe the general characteristics of this catalogue, perform a series of tests on the data and briefly compare our detections to existing optical and X-ray-detected clusters.

After applying the magnitude limits described in §3.7.1 a source catalogue of 69,797 galaxies is analysed by the algorithm. We find a total of 97 clusters, identifying a total of 1293 cluster galaxies (0.5% of the original galaxy sample) and 813 associate cluster members (candidate cluster members that were not selected). Of these clusters, 34% were detected in $\{g-r, r-i\}$ and 66% in the $\{r-i, i-z\}$ combinations.

Although we define a blue limit for the $g-r$ colour-magnitude relation ($c_{m20}>0.47$), equivalent limits were not applied to the $r-i$ and $i-z$ colours. We can however place upper bounds on the blue limit in these colours by noting no clusters were detected below $r-i=0.24$ and $i-z=0.18$. Such limits serve to reduce the search time for future survey scans.

Table 3 shows an extract of the cluster catalogue. This 7 square degree sample of 97 Stripe 82 clusters is available online\footnote{http://orca.dur.ac.uk/}.

Finally, we set the minimum membership of a cluster, $N_{\text{min}}$, to five galaxies.
Table 3. A sample of the ORCA cluster catalogue generated in this study. Full details of the columns can be found in Table 3. The first column contains the cluster name based on the IAU convention. Columns 2 and 3 note the J2000 estimated cluster positions in degrees. Columns 4 and 5 describe the cluster redshift and source data used to calculate the redshift. Column 6 notes how many members were found in the cluster, and we provide estimates for the cluster $B_{gc}$ richness and sequence scatter in Columns 7 and 8. The final two columns indicate the ratio (in degrees) of 80% of the cluster members and the ratio of this value to the 20% radius, a measure of cluster concentration.

| Name                  | RA        | DEC       | cluster_x | cz_type | $N_{gal}$ | $b_{gc}$ | scatter | $\theta_{80}$ | C   |
|-----------------------|-----------|-----------|-----------|---------|-----------|----------|---------|---------------|-----|
| MGB J234017-00030.9   | 355.06912 | -0.06455  | 0.245     | c0s0w0q0d0b0p6h2 | 6         | 19416    | 0.047   | 0.0001        | 1.700 |
| MGB J233817+00190.0   | 354.56897 | 0.3309    | 0.208     | c0s0w0q0d0b0p8h6 | 8         | 94461    | 0.038   | 0.0003        | 3.667 |
| MGB J234113-00000.0   | 355.30349 | -0.0597   | 0.166     | c0s0w0q0d0b0p6h2 | 6         | 182181   | 0.018   | 0.0003        | 1.692 |
| MGB J234400-00300.3   | 355.99952 | -0.50461  | 0.181     | c0s1w0q0d0b0p5h4 | 6         | 71831    | 0.025   | 0.0001        | 1.750 |
| MGB J234725+00190.7   | 356.85322 | 0.32867   | 0.201     | c0s0w1q0d0b0p14h14 | 14        | 10967    | 0.037   | 0.0004        | 2.545 |

4.2 Cluster positions & redshifts (cluster_x, cz_type)

The ra and dec position quoted in the catalogue is the algorithm estimate of the centre of each cluster, based on the average positions of their members.

Although we do not use any redshift data to generate our cluster catalogue, we provide redshift estimates for each system detected by the algorithm. These redshifts are weighted towards members with spectroscopic data, but two sets of photometric redshift data (hyperz and the DR7 photometric estimate) are used to provide each cluster galaxy with at least one redshift estimate. From the catalogue of 1293 cluster galaxies, 2.6% have spectroscopic data (DR7 spectroscopic redshifts, WiggleZ and 2SLAQ), 93% have DR7 photoz and 87% have hyperz estimates. The hyperz estimates for cluster members were generated using only S0 and E SEDs, a Calzetti et al. (2000) reddening law and a two-stage conversion (over and above that performed by hyperz) to the redshift where a range identified in coarse redshift bins is re-sampled with a smaller bin width. Comparing these estimates to available spectroscopic redshifts, the measured error dispersions are higher in hyperz than in the DR7 pipeline (0.029 vs 0.016).

We calculate each cluster redshift by determining the weighted median redshift from the available member data. The weighting for a spectroscopic, DR7 photoz and hyperz redshift is 4, 2, 1 respectively, the higher weighting for DR7 photoz reflecting the smaller error dispersion mentioned above. To gauge the accuracy of our redshift estimate, we note the calculated redshift of Abell 2631 is $z = 0.26$, some 0.02 lower than the value determined by $z = 0.28$ Böhringer et al. (2000). The median cluster redshift of the whole catalogue is $z_{med} = 0.31$, and the maximum redshift is $z = 0.57$. Approximately 25% of the clusters have at least one member with a spectroscopically measured redshift.

Without access to spectroscopy, accurate photometric redshifts of red sequence cluster galaxies are good measures of cluster redshifts. We quantify this in Figure 3 by comparing the photometric and spectroscopic redshifts of cluster BCGs from a sample of the full GMB11 Stripe 82 cluster catalogue with spectroscopic redshifts. After removing a small systematic trend in $\sigma_z$ outliers, the $1\sigma$ dispersion in $(z_s - z_p)/1 + z_i$ is 0.0157 (increasing to 0.0163 when ignoring the systematic error). This suggests BCG photometric redshifts are accurate estimates of the cluster redshift.

The cz_type property is a shorthand description of the available redshift data for each cluster, each letter defining a measurement type, followed by the number of that type. The letters denote data from the mo(c)k, DR7 (s)pectroscopic, (w)iggleZ, 2SLA(q), DR7 (p)hotometric and (h)yperz datasets, where mock is of course not used in this observational data.

4.3 Cluster richness ($B_{gc}$)

With access to cluster redshifts we are able to calculate the $B_{gc}$ optical cluster richness, a robust parameter known to correlate with cluster mass. We use the $B_{gc}$ measure described in Yee & López-Cruz (1999):

$$B_{gc} = \frac{\rho_{bg} D(z_c) \gamma^{\alpha}}{I, \Phi(M_3, M_3 + 3, z_c)}$$

(3)

where $\rho_{bg}$ is the background surface density of all source catalogue galaxies (irrespective of their colour) inside a $0.5 \, h^{-1} \, \text{Mpc}$ radius with luminosities between the third brightest cluster galaxy ($M_3$) and three magnitudes fainter. The integrated luminosity function, $\Phi(M_3, M_3 + 3, z_c)$, is measured over the same luminosity range. We evolve the $z=0.1$ Blanton et al. (2003) SDSS r-band luminosity function ($\phi_c = 1.49 \times 10^{-2}, M_c = -20.44, \alpha = -1.05$) using the prescription described in Lin et al. (1999) that adds redshift-dependent terms to $\phi_c$ and $M_c$ with parameters $P = 1.06$ and $Q = 1.82$. D, the angular diameter distance, is derived from the cluster redshift $z_c$, $\gamma$ and $I_c$ respectively define the slope of the angular galaxy correlation function and the integration constant arising from de-projecting the cluster. We set these to $\gamma = 1.77$ and $I_c = 3.78$. The correlation amplitude $A_{gc}$ is defined as:

$$A_{gc} = \frac{N_{net} (3 - \gamma)}{2 \theta^\gamma}$$

(4)

where $N_{net}$ is the background-corrected count of galaxies within the luminosity range described above, out to an angular separation $\theta$ that corresponds to $0.5 \, h^{-1} \, \text{Mpc}$ at the cluster redshift. $N_{bg}$ is the background galaxy count within this radius, estimated from the mean density of galaxies across the whole field. The full 270 deg$^2$ Stripe 82 catalogue provides additional definitions of cluster richness - we refer readers to GMB11 for the details of those measurements.

4.4 Cluster sequence scatter (scatter)

To estimate the width of a detected cluster’s sequence, we first make a fit to the slope of the sequence and remove the tilt. Using cluster members between $m_{BCG} \leq m \leq m_{BCG} + 3$, we estimate the sequence scatter by making a $2\sigma$ clip in the colour distribution.

The robustness of the red sequence fit is sensitive to the number of members in the detection. Based on a bootstrap-resampling of the cluster sequences, we find the fitting procedure is robust in clusters with at least 8 members. Below this, sequence scatter estimates are dominated by fitting uncertainty. For systems of at least 10 members, the characteristic error in the sequence scatter is 34%, dropping to 19% for clusters with up to 30 members and 8% for...
those with at least 50 members. Future catalogues will provide improved estimates of the sequence-fitting error.

4.5 Projected scale ($\theta_{80}$) & concentration ($C$)

For each cluster, a projected scale size $\theta_{80}$ is provided. This is calculated as the angular radius (in degrees) enclosing 80% of cluster members from the centre.

A measure of the projected concentration ($C$) is determined by comparing the radius enclosing 80% of the cluster members to the radius enclosing 20%. High values of $\theta_{80}/\theta_{20}$ indicate a centrally concentrated cluster.

4.6 Testing the algorithm

4.6.1 Cluster re-detection robustness

To determine how robust the detector is to catalogue incompleteness, we attempt re-detections of the Abell 2631 cluster after removing a random selection of members from the source data. Our sole constraint is that the cluster BCG remains in the source data. In the following analysis, we only consider the detected cluster closest to the original Abell 2631 position. Robustness is defined as the fraction of members detected in the new cluster from those remaining in the input catalogue. We use a test $g$-$r$ photometric filter that adopts a $\beta_{g-r}$, $c_{\min}$ and $\sigma_{g-r}$ best suited to the recovery of A2631, selecting approximately 85% (108) of the visually selected members. We experiment with removal fractions down to 95%, corresponding to the largest fraction still retaining $N_{\min}=5$ original cluster members in the sample.

Fifty random realisations of a depleted input catalogue are generated for each removal fraction, yielding a median recovery rate based on members that could have been added to the cluster. The solid blue line in Figure 9 shows how increasing the removal fraction affects the fraction of cluster members recovered; error bars on this line represent 1σ uncertainties from the 50 re-detections in each bin. The recovery fraction when no galaxies have been ejected is $\sim 93\%$ of the 108 A2631 members located inside the photometric filter. The other 7% were rejected by the algorithm because either their Voronoi cells have insufficient densities to join the overdense collection of cells ($P_{\text{thresh}}$, see 3.7.2), or their inclusion causes the percolating cluster to drop below the critical density ($\Sigma_{\text{crit}}$).

We take into account this intrinsic detection inefficiency, quoting yields from the cluster re-detection relative to the $\sim 93\%$ of members recovered where no additional galaxies are removed. Unsurprisingly, the fraction of detected members located in the clustered drops as more members are excised. However, over 75% of remaining members are re-detected even after half of the cluster is removed. Approaching larger removal fractions, the fragmentation of cluster members into spatially distinct groups hinders recovery of the complete set. The black dashed line in this plot corresponds to the minimum recovery fraction required to identify $N_{\min}=5$ original members from the input data. The algorithm can robustly identify the original cluster down to an 80% removal fraction, corresponding to 22 of the original 108 galaxies. Below this limit, an insufficient number of cluster members are recovered by the detector to identify a cluster associated with the halo.

For each ejection fraction we also calculate the recovery accuracy: the fraction of visually identified A2631 galaxies making up the re-detected cluster. The dotted blue line in Figure 9 shows this parameter. The initial accuracy (no members are removed) is approximately 60%, providing some estimate of our level of incompleteness when visually identifying cluster membership. As more members are removed, there is a gradual reduction in accuracy, implying replacement of these members with other galaxies becomes
more commonplace. At large (> 70%) removal fractions, fragmentation acts to reduce the connectivity of cluster members, increasing the number of contaminant galaxies that share the photometric filter.

4.6.2 Cluster displacement and edge effects

A cluster detector should identify systems irrespective of the projected environment they are located in. Ideally then, recovery of identified members is achieved even if the system is moved to another position.

To determine the sensitivity of cluster identification to localised background fluctuations, we shift source data positions of known cluster members to a random location, keeping their spatial distribution intact. A buffer is created around the survey edge to ensure no cluster members are displaced outside the boundaries, then a re-detection of the cluster is attempted. The re-detection performance is quantified by the recovery efficiency - the fraction of original members in the new cluster, and the recovery accuracy remains as defined in the previous test.

Figure [10] shows the recovery efficiency (solid blue line) and recovery accuracy (dotted blue line) for clusters spanning more than an order of magnitude in membership (N_{min}=5 to 174 galaxies). If there was a choice of cluster for a membership bin, we used the system with the smallest sequence scatter to determine the impact of displacement on the best candidate in that membership group. Each cluster was re-detected in the pair of selection filters it was originally identified in, meaning a re-detection with no displacement would yield a perfect recovery efficiency and recovery accuracy (both equal to unity). We perform 50 random displacements for each of the selected clusters, using their scatter to derive 1σ uncertainties from the mean. The black dashed line in Figure [10] corresponds to the recovery fraction required to detect N_{min}=5 galaxies of the original system from each displaced cluster.

For the majority of cluster sizes, recovery accuracies are approximately constant at ~ 90%, meaning 10% of the cluster members are background galaxies selected in the same photometric selection. Recovery efficiency data suggest the detector makes significant cluster re-detections for systems down to 10 members, but smaller groups are susceptible to higher levels of contamination and fragmentation. Our example case of Abell 2631 (at log_{10}N_{gal} ∼ 2.1), with a recovery efficiency of 80% is approximately 13% lower than the recovery fraction from robustness test calculated above. A recovery accuracy of ~86% is consistent with the detector swapping 13% of original members with background galaxies when the cluster is moved.

We next establish how survey edges bias the detection of systems at the boundaries. Using the same set of clusters, we repeat the above experiment, specifically placing systems close to the survey edges to quantify the impact of edge effects on group and cluster recovery. When moving each cluster, we ensure no members are outside of the survey boundary. The average separation between survey edge and the member furthest from the cluster centre is around 23 arcseconds.

Galaxy cells at the boundary of a Voronoi Diagram are unbounded, often resulting in very large cell areas. This may hamper the identification of low-membership clusters, where a member with cell area exceeding the probability threshold may preclude the cluster from detection. Random positions are selected along any one of the four sides of the survey (allowing clusters to reside in a corner). In our source catalogue, the declination boundaries (at δ = ±1.25°) are set by the geometry of the stripe, whilst the RA boundaries are artificially defined. Distances between the cluster centroid and survey edge are large enough to include all members within the survey. The red line in Figure [10] shows the recovery efficiency based again on 50 randomised displacements. This distribution is very similar to that of the displacement test above, suggesting edge effects do not hinder the recovery of clusters any more than the displacement of the members themselves. This is particularly significant at group scales, where the exclusion of one or two members could prevent the detection of the system.

4.6.3 False positive detection rate

We set the detector the task of attempting to detect spatially clustered systems with randomised colours. This establishes the importance of red sequences to cluster detection with this algorithm and provides an estimate of the false detection rate. We run the detector on the source catalogue in the same manner as before, having first shuffled the colours so while cluster members still reside in high surface density regions, they no longer have red-sequences. We identified two “clusters” (with 5 and 6 members) in the 7 square degree survey, both located at the positions of original high membership ORCA clusters. To ensure this calculation is uninfluenced by the size of the survey, we repeat this process on the full Stripe 82 dataset (−50° < α < 50°) covering 270 square degrees. The algorithm detects 15 “clusters” from these data, each consisting of five or six-member groups. From this we infer the number of spurious systems detected per 7 square degrees is 0.39.

In a similar fashion we next randomise galaxy positions while keeping the colours the same. This means cluster red-sequences remain intact as the algorithm scans through colour-magnitude space, but points clustered in colour are no longer clustered in the sky.
algorithm detected four “clusters” over the full 270 square degree Stripe 82 dataset, implying a \( \sim 0.1\% \) spurious cluster detection rate.

Both exercises suggest the detector cannot identify clusters without correlations in both colour and spatial position. Moreover the probability of detecting systems based on random distributions of both colour and position is below 1%.

4.6.4 Projected cluster-pair resolution

The ideal algorithm can identify two clusters with the same angular position on the sky, but at different radial distances. Using the \( \epsilon_{\text{cmax}} - z \) relation demonstrated in Figure 2, one can in principle isolate superimposed systems by identifying them in different filters. Within a detection filter \( f(C_{\lambda}) \) of width \( \sigma_f \), two spatially coincident systems will be merged even if their sequences do not directly overlap. We overcome this limitation by splitting sequences in the following colour (\( C_{\lambda} \)) with the application of joint filters (\( C_{\lambda} \)). The resolving power of the algorithm in projection is therefore limited by the merging of separate clusters that are mistaken as multiple detections in \( C_{\lambda} \).

We test this effect with the same clusters used in 4.6.2 by implanting a 7-member test cluster at the same spatial position and colour normalisation \( \epsilon_{\text{cmax}} \). We increase the test cluster \( C_{\lambda} \) colour normalisation by \( \delta \epsilon_{\text{cmax}} \) and run the matching algorithm. This is repeated until the detector classifies the reddened test cluster as an normalisation by colour normalisation implanting a 7-member test cluster at the same spatial position and angular position on the sky, but at different radial distances. Using the ideal algorithm can identify two clusters with the same angular position on the sky, but at different radial distances. Using the \( \epsilon_{\text{cmax}} - z \) relation demonstrated in Figure 2, one can in principle isolate superimposed systems by identifying them in different filters. Within a detection filter \( f(C_{\lambda}) \) of width \( \sigma_f \), two spatially coincident systems will be merged even if their sequences do not directly overlap. We overcome this limitation by splitting sequences in the following colour (\( C_{\lambda} \)) with the application of joint filters (\( C_{\lambda} \)). The resolving power of the algorithm in projection is therefore limited by the merging of separate clusters that are mistaken as multiple detections in \( C_{\lambda} \).

We test this effect with the same clusters used in 4.6.2 by implanting a 7-member test cluster at the same spatial position and colour normalisation \( \epsilon_{\text{cmax}} \). We increase the test cluster \( C_{\lambda} \) colour normalisation by \( \delta \epsilon_{\text{cmax}} \) and run the matching algorithm. This is repeated until the detector classifies the reddened test cluster as an normalisation by colour normalisation implanting a 7-member test cluster at the same spatial position and angular position on the sky, but at different radial distances. Using the ideal algorithm can identify two clusters with the same angular position on the sky, but at different radial distances. Using the \( \epsilon_{\text{cmax}} - z \) relation demonstrated in Figure 2, one can in principle isolate superimposed systems by identifying them in different filters. Within a detection filter \( f(C_{\lambda}) \) of width \( \sigma_f \), two spatially coincident systems will be merged even if their sequences do not directly overlap. We overcome this limitation by splitting sequences in the following colour (\( C_{\lambda} \)) with the application of joint filters (\( C_{\lambda} \)). The resolving power of the algorithm in projection is therefore limited by the merging of separate clusters that are mistaken as multiple detections in \( C_{\lambda} \).

We note the ORCA cluster (MGB J234341+00180.3) is situated between the western pair (BCG J234322+00190.6 and BCG J234403+00130.6). Optical-band imaging (Figure 16 in Appendix) shows evidence of early type galaxies distributed in a filamentary chain, approximate comoving length \( 2h^{-1}\text{Mpc} \), sampled by ORCA between the maxBCG detections.

The other pair (BCG J234106+00120.4 and BCG J234122+00190.0) may be part of an elongated structure sampled by both the four maxBCG entries in that area and also by the ORCA detector. Figure 17 shows the ORCA cluster MGB J234105+00180.3. This cluster centre, situated between the two maxBCG clusters, matches the centroid of an RASS cluster to within \( 0.4' \), with an uncertainty of \( \sim 1' \) in the X-ray source.

Overall, we find very good agreement with the maxBCG catalogue of clusters, detecting 81% of their entries in the survey region, rising to 100% when taking into account how the different algorithms handle systems that by eye resemble filamentary structure.

5.2 X-ray detected clusters

X-ray selected cluster catalogues are useful independent checks on the population of clusters detected by optical cluster-finders. We use cluster data from the ROSAT All Sky Survey-derived (RASS; Voges et al. 1999) ORAS (Böhringer et al. 2000) and BCS catalogues (for the latter, both main and extended catalogues; Ebeling et al. 1998 2000), the XCS (Romer et al. 2001), the BCGs (Arkhipova et al. 2011) and BLOX (Dietrich et al. 2007) from XM-M-Newton, and ChAmp (Barkhouse et al. 2006) from Chandra. We combine these datasets, taking care to identify any duplicate detections, to form an X-ray catalogue consisting of 1463 unique clusters. From this catalogue there are 58 X-ray clusters within the full 270 square degree footprint covered by Stripe 82, and two of these lie within the 7 square-degree sample studied here. In future we will provide a comparison of these X-ray data to an optical cluster catalogue covering a larger area.

Blue squares in Figure 11 show the position of the two clusters in the region we study here. The westernmost X-ray cluster, RXC J2337.6+0016 (also detected in the flux-limited Brightest Cluster Sample; Ebeling et al. 1998) is the X-ray counterpart to ACO2631 (Abell, Corwin & Olowin 1989) and has a redshift of 0.2780 (Crawford et al. 1995). The X-ray position coincides with the ORCA detection of this system (MGB J233740+00160.2; \( z = 0.2571 \)) at
Table 4. An extract from the Koester et al. (2007a) catalogue noting the 22 maxBCG clusters within the limits of this SDSS sample field. The cluster name follows the IAU JHHMMSS+DDMM.s format. The RA and DEC are J2000, and measured in degrees. \( z_{\text{photo}} \) and \( z_{\text{spec}} \) are the estimated photometric and spectroscopic redshifts of the clusters. \( N_{\text{gal}} \) is the number of members in the cluster, and \( N_{\text{R200}} \) is the scaled richness.

| Cluster name | RA     | DEC    | \( z_{\text{photo}} \) | \( z_{\text{spec}} \) | \( N_{\text{gal}} \) | \( N_{\text{R200}} \) |
|--------------|--------|--------|------------------------|------------------------|---------------------|---------------------|
| BCG J233740+00160.3 | 354.41553 | 0.27138 | 0.286 | 0.277 | 59 | 88 |
| BCG J234624+00440.0 | 356.59955 | 0.74943 | 0.273 | 0.275 | 25 | 26 |
| BCG J233746-00420.2 | 354.44067 | -0.70310 | 0.286 | 0.287 | 20 | 17 |
| BCG J234100+00040.9 | 355.24905 | 0.08161 | 0.194 | 0.185 | 23 | 23 |
| BCG J233955-00250.0 | 354.97916 | -0.43282 | 0.275 | 0.277 | 17 | 15 |
| BCG J234548-01070.7 | 356.45068 | -1.12775 | 0.273 | - | 18 | 18 |
| BCG J234604-00100.0 | 356.51477 | -0.18283 | 0.254 | - | 22 | 22 |
| BCG J234322+00190.6 | 355.84039 | 0.32587 | 0.257 | 0.267 | 38 | 60 |
| BCG J234146+01070.5 | 355.44077 | 1.12444 | 0.246 | 0.251 | 15 | 11 |
| BCG J233919-00150.6 | 354.82941 | -0.25941 | 0.284 | - | 14 | 11 |
| BCG J234024-00050.6 | 355.10205 | -0.09300 | 0.281 | - | 17 | 13 |
| BCG J234720+00290.7 | 356.83487 | 0.49456 | 0.286 | 0.275 | 12 | 10 |
| BCG J233900+00420.0 | 357.75143 | 0.71610 | 0.219 | 0.183 | 14 | 11 |
| BCG J234122+00190.0 | 355.34253 | 0.33330 | 0.284 | 0.278 | 22 | 22 |
| BCG J233911-01130.3 | 354.79459 | -1.22236 | 0.292 | - | 14 | 10 |
| BCG J234626+00430.7 | 356.60690 | 0.72794 | 0.251 | - | 25 | 29 |
| BCG J234603+00130.6 | 356.01273 | 0.22646 | 0.262 | - | 16 | 11 |
| BCG J234233-00170.3 | 355.63776 | -0.28873 | 0.275 | - | 16 | 14 |
| BCG J233755+00130.5 | 354.47760 | 0.22478 | 0.262 | 0.278 | 37 | 61 |
| BCG J233825-00090.2 | 354.60291 | -0.15397 | 0.270 | - | 14 | 11 |
| BCG J234737-00370.9 | 356.90375 | -0.63221 | 0.262 | - | 14 | 11 |
| BCG J234106+00120.4 | 355.27640 | 0.20707 | 0.262 | - | 15 | 10 |

6 PS1 MOCK CLUSTER CATALOGUE

6.1 Simulations

In this section, we describe the application of ORCA to a mock PS-1 lighthouse. Theoretical simulations allow one the luxury of comparing clusters detected by the algorithm (ORCA clusters) to the galaxy membership of dark matter haloes (hereafter \( \Lambda \)CDM clusters). Simulated galaxies are allocated to dark matter haloes using the Bower et al. (2006) semi-analytic model. This approach makes the assumption a satellite galaxy is stripped of hot gas immediately following accretion onto a large halo. Star formation is halted after the cold gas reservoir is depleted, and the galaxy joins the red sequence. Coupled with AGN feedback, this prescription reproduces the observed bimodality in galaxy colours. However a known flaw, the rate of gas depletion, results in redder than observed satellite galaxies. Recent treatments of ram-pressure stripping (e.g., McCarthy et al. 2008) hope to improve understanding of the transition to early-type galaxies with improved semi-analytic models (Font et al. 2008; Benson & Bower 2010).

Although mock surveys are inaccurate realisations of the universe (see Hilbert & White 2010, for an example in a cluster detection context), they can nevertheless serve as self-consistent tests of the detector. We emphasise, however, there is little merit in comparing mock cluster detections with those in survey data until models can reproduce the observed group and cluster galaxy population with more fidelity.

To compare ORCA detections to the model, we construct \( \Lambda \)CDM clusters with the aid of halo memberships and full 3D galaxy data. In each \( \Lambda \)CDM cluster, we calculate the approximate centre from cluster member positions. Outlier galaxies are identified by rejecting 3\( \sigma \) deviations from a bootstrap-estimated median galaxy-centroid distance. Following outlier ejection, we find the resultant cluster sizes agree well with the virial radii of the host haloes. We set a minimum cluster mass limit by selecting \( \Lambda \)CDM clusters residing in haloes with \( M_{h} \geq 10^{15} h^{-1} M_{\odot} \).

6.2 Mock reference cluster

We select a “reference cluster” from a set of \( \Lambda \)CDM-based detections generated from a preliminary scan of the simulation. The chosen cluster allows us to set the slope and width of the photometric filters in our search through the mock data. Candidate training clusters were identified from a redshift range bracketing Abell 2631 (\( z = 0.278 \)), with similar memberships and a clear sequence in all colours. We selected the richest of these candidates, featuring 130 members and a redshift of \( z = 0.3 \). By applying the same fitting techniques as those described in 3.7.1, we set the filter parameters listed in Table 8 and apply the same colour ranges as those used on the SDSS. The fitted gradients are steeper in \( g-r \) than \( r-i \), with similar memberships and a clear sequence in all colours. The values were nevertheless consistent with the other candidate reference clusters identified in the mock. As before, we use the most conservative width (\( g-r, 0.13 \)) for filters in each colour.
Figure 11. Clusters detected in the Stripe 82 field. The coloured cells represent clusters detected in different colour pairs. Blue cells correspond to clusters detected in \(\{g-r, r-i\}\) filter pairs, red clusters detected in \(\{r-i, i-z\}\) filter pairs. Yellow cells indicate the BCG position of each cluster. Red circles indicate the position of maxBCG clusters, based on data shallower than that used in the study here. Circle radii correspond to \(1h^{-1} Mpc\), based on the maxBCG photometric redshift estimate of the cluster. Dashed red circles indicate the four maxBCG clusters discussed in \(\S\) 5.1 that also feature gri-colour imaging in Figures 16 and 17. Blue squares note the position of ROSAT All Sky Survey X-ray sources, with half-lengths corresponding to \(1h^{-1} Mpc\).

Table 5. Filter parameters fitted from the mock reference cluster (by analogy with those derived from Abell 2631) along with colour ranges searched by the detector (the same as those used in the Stripe 82 data).

| Colour | Slope (\(\beta\)) | Width (\(\sigma\)) | Range         | Filters |
|--------|------------------|--------------------|---------------|---------|
| g-r    | -0.070           | 0.130              | 0.47 – 2.00   | 39      |
| r-i    | -0.032           | 0.064              | 0.00 – 1.22   | 38      |
| i-z    | -0.012           | 0.035              | -0.10 – 1.10  | 31      |

6.3 Producing \(\Lambda\)CDM and mock ORCA cluster catalogues

Except for the revised parameters listed in Table 5, the detector ran as described in [3] and applied magnitude limits created a source catalogue of 80,536 mock galaxies. Because the algorithm relies on the detection of colour-magnitude ridgelines, we do not want to include \(\Lambda\)CDM clusters without detectable sequences. We therefore construct the \(\Lambda\)CDM cluster list from galaxies selected in the same photometric filters used by the detector, meaning \(\Lambda\)CDM clusters may also be detected multiple times. We group together \(\Lambda\)CDM clusters with common halo identifiers, but as before selected the highest reduced flux candidate as the “best” \(\Lambda\)CDM cluster.

We found a total of 305 ORCA clusters with \(M_H \geq 10^{13} h^{-1} M_{\odot}\); at \(M_H \geq 10^{14} h^{-1} M_{\odot}\) the counts are more equal. Although the majority of clusters identified are at \(z \sim 0.3\), the tests we describe in the following section will highlight how well ORCA performs over this entire parameter space. Figure 12 shows a simple comparison of the two catalogues by plotting both sets of clus-
clusters residing in haloes $M_h \geq 10^{13.5} h^{-1} M_\odot$ out to $z = 0.6$ (the highest cluster redshift in the SDSS cluster catalogue). Grey circle centres denote the position, and their radii the maximum member-cluster centre distance of $\Lambda$CDM clusters. Blue and red cells represent ORCA clusters detected in $\{g-r, r-i\}$ and $\{r-i, i-z\}$ respectively.

6.4 Performance of the algorithm

To determine how well the detector recovers and characterises the mock clusters, we illustrate here three simple tests to quantify the detection performance.

6.4.1 Completeness

We define completeness as the number of detected haloes as a function of halo mass and redshift. A halo is detected if at least $N_{\text{min}}$ galaxies are identified, even if they are shared between multiple ORCA clusters (for example, fragmenting a halo when the algorithm attempts to identify substructure). We compare this number to $\Lambda$CDM cluster counts (by definition unfragmented), with at least $N_{\text{min}}$ members.

The fraction of detected $\Lambda$CDM clusters can be seen in Figure 13 where we produce a grid of cells with sampling intervals of 0.05
in redshift and 0.2 in \( \log_{10} \) halo mass. Because in some cases only a few detections occupy each cell, some regions will suffer from shot noise. We smooth the data using a 3 \times 3 grid so the completeness for a given cell is the mean completeness over this region. Empty regions in Figure 13 therefore indicate where either no \( \Lambda \mathrm{CDM} \) clusters exist or too few clusters are found to reliably calculate the completeness (we set a threshold of at least five clusters detected over the 3 \times 3 grid). Between 0.1 \( \leq z \leq 0.4 \), the detector attains at least 68\% completeness for halo masses above \( 10^{13.8} h^{-1} M_\odot \), and is over 90\% complete in halo masses exceeding \( 10^{14.3} h^{-1} M_\odot \). This compares favourably with the \texttt{maxBCG} algorithm applied to mock simulations, where Koester et al. (2007) report > 90\% completeness between 0.1 \( \leq z \leq 0.3 \) for \( M_H \geq 10^{14.1} h^{-1} M_\odot \) with clusters containing at least 10 members (cf. \( N_{\text{min}}=5 \) in this study). Applying the completeness definition and the same selection criteria as that study, the \texttt{ORCA} detector is > 90\% complete down to a halo mass of \( 10^{13.8} h^{-1} M_\odot \). These results also compare well to the Voronoi Tessellation completeness of the \texttt{2TessX} (Van Breukelen & Clewley 2009) algorithm, either matching or exceeding their stated completeness for \( M_H = 10^{13.7} h^{-1} M_\odot \) up to our redshift limit.

At higher redshifts there is a decline in completeness where there are only a few members brighter than the magnitude limit, reducing the algorithm sensitivity to distant clusters. This effect is more apparent among the lower mass haloes. At high redshift (\( z > 0.4 \)) and low mass (\( M_H \leq 10^{13.5} h^{-1} M_\odot \)) there are 12 \( \Lambda \mathrm{CDM} \) clusters, but the detector identifies only two of these. We also note a local incompleteness at \( z \leq 0.08 \). Arising from our choice of probability threshold (\( P_{\text{thresh}} \)), too few overdense cells are selected in filters featuring low signal-to-noise clusters. The photometric filters best suited to detecting local, relatively blue clusters have galaxy populations dominated by the blue cloud component of the colour-magnitude relation. Successful detections in this crowded field are compounded by the larger scale-size of more local clusters such as the local (\( z = 0.03 \)) seven-member group at the north-western boundary of the catalogue in Figure 13. Under these circumstances, it becomes unlikely cluster Voronoi cells share common vertices, restricting potential membership links between them.

We classify spurious detections in the mock cluster catalogue as those clusters where each member belongs to a different halo. Of the 305 \texttt{ORCA} clusters, only two fit this description, suggesting a spurious detection rate (0.7\%) consistent with tests performed in 4.6.3.

### 6.4.2 Stellar mass accuracy

Stellar mass accuracy is the stellar mass of an \texttt{ORCA} cluster relative to that of the \( \Lambda \mathrm{CDM} \) cluster belonging to the same halo. Because the algorithm may split the halo galaxies into multiple clusters, we combine the mass of all \texttt{ORCA} clusters sharing the same halo. In \( \Lambda \mathrm{CDM} \) clusters with up to \( \sim 12 \) members (approximately 75\% of the catalogue), over half of the total cluster stellar mass comes from the two most massive galaxies. The efficient detection of these galaxies is therefore essential in gaining accurate estimates of cluster stellar masses. The stellar mass accuracy for each \( \Lambda \mathrm{CDM} \) cluster is \( \Delta_A = M_{\odot}^* / M_{\odot}^\text{true} \), where \( M_{\odot}^* \) is the stellar mass of all \texttt{ORCA} cluster members registered to the \( \Lambda \mathrm{CDM} \) cluster’s halo. We apply the same gridding technique discussed in the previous section, requiring at least 5 clusters in a grid to define a reliable \( \Delta_A \). As Figure 14 shows, between 0.1 \( \leq z \leq 0.4 \) the algorithm recovers over half of the cluster stellar mass for systems with halo masses of at least \( 10^{13.4} h^{-1} M_\odot \). This recovery fraction improves with increasing mass, reaching 90\% in some cases. Both local and distant clusters suffer from lower stellar mass estimates. For the former, higher levels of halo fragmentation (one halo being assigned to many \texttt{ORCA} clusters) result in galaxies lost to nearby systems with densities or memberships too low to qualify as clusters. Those systems with redshifts \( z > 0.5 \) tend to be unfragmented but contain fewer members, causing an underestimation of cluster stellar mass. The stellar mass accuracy at the median redshift of the survey (\( z = 0.33 \)) remains above 50\% down to halo masses of \( 10^{13.2} h^{-1} M_\odot \), and above 75\% from masses of \( 10^{13.8} h^{-1} M_\odot \), suggesting the detector performs well in estimating the true cluster stellar mass content.

![Figure 13](image1.png) Completeneess of mock \( \Lambda \mathrm{CDM} \) clusters. The fraction of correctly detected clusters from the ORCA catalogue as a function of halo mass and redshift. The white regions indicate where there were no \( \Lambda \mathrm{CDM} \) clusters in that bin.

![Figure 14](image2.png) Stellar mass accuracy. The fraction of recovered stellar mass in mock clusters as a function of halo mass and redshift.
scheme introduced in redshift and halo mass, the gridding method here being the same fraction. Figure 15 shows the purity of ORCA is considered pure, instead directly assigning each cluster a purity. However, we decide not to adopt a threshold above which a cluster is in line with the purity described by Koester et al. (2007b). As discussed in §6.4.1, a halo is detected by the algorithm if it finds at least $N_{\text{min}}$ members that have been allocated to ORCA clusters. For a cluster with 7 members, the distinction between a cluster containing 5 halo galaxies and 2 interlopers and one containing 7 halo galaxies provides a measure of cluster purity. We define purity as the fraction of galaxies ORCA assigned to the cluster that are members additionally belonging to the host halo. This description is in line with the purity described by Koester et al. (2007b). However, we decide not to adopt a threshold above which a cluster is considered pure, instead directly assigning each cluster a purity fraction. Figure 15 shows the purity of ORCA clusters with varying redshift and halo mass, the gridding method here being the same scheme introduced in §6.4.1. ORCA clusters are at least 70% pure at the median redshift of the survey over all halo masses. The purity appears to drop at higher redshifts, attributed to faint but genuine cluster members being replaced by brighter contaminants that lie on the cluster sequence. Relative to the completeness and stellar mass estimates, cluster purity is not as sensitive to halo mass. This is most likely a consequence of the membership incompleteness discussed in §7.2. Because peripheral members are less likely to be in Voronoi cells tagged as statistically significant, the inclusion of interlopers at cluster edges is reduced. As in the previous section, increased halo fragmentation drives the local drop in purity, serving to increase the contamination fraction by distributing the halo galaxies among local clusters and systems failing to achieve cluster status.

6.4.3 Purity

7 SUMMARY

We present and demonstrate a new cluster detection algorithm based on red-sequence cluster searches, the detection of overdensities using Voronoi Tessellations, and connecting galaxies into clusters with a Friends-of-Friends algorithm. With this approach, we make only two assumptions about the systems we are looking for: that they have detectable red-sequences, and are overdensities in the projected plane of the sky.

We calibrate the photometric selection filters to a rich Abell cluster found in SDSS data, and find that recovery of members from both this large cluster and a small group is largely insensitive to the choice of two algorithm parameters controlling the behaviour of the algorithm. When applying the algorithm to a sample of SDSS Stripe 82 galaxies with four bands, we find 97 clusters. Based on spectroscopic and photometric redshifts, we estimate these clusters are detected out to $z = 0.6$ and the catalogue has a median redshift of $z = 0.31$. We perform false-positive tests suggesting the spurious detection frequency is below 1%. Tests on the catalogue suggest the detector is robust to sparsely sampled cluster fields and is not overly sensitive to survey edges. In comparing our data to existing optical and X-ray clusters, we find good agreement with the maxBCG and RASS catalogues in the same region.

We go on to test the performance of the detector with a mock survey generated from a semi-analytic galaxy formation model. In comparing the ORCA cluster detections to those generated from halo membership data, we make a quantitative assessment of the detector performance. The algorithm identifies 305 clusters, whilst the simulation produces 414 down to a halo mass of $10^{13}h^{-1}M_\odot$. At the median redshift of the catalogues (both $z = 0.33$) we find ORCA is 75% complete down to a cluster halo mass of $10^{13.4}h^{-1}M_\odot$ and is able to recover approximately 75% of the total stellar mass for clusters in haloes of at least $10^{13.8}h^{-1}M_\odot$.

We have demonstrated this algorithm is capable of identifying clusters in both real and simulated data with minimal assumptions as to the nature of clusters. In combining comprehensive colour scans to search for cluster red-sequences with Voronoi diagrams to estimate surface densities, we avoid making model-dependent decisions about what a cluster is. Cluster redshifts arise as a consequence, not condition, of our detection, affording additional freedom from model SEDs and the uncertainties inherent in photometric redshift data spanning the depths, fluxes and areas set to be commonplace in next-generation galaxy catalogues. This detector can be used in any survey where there are at least two photometric bands, but is most powerful when applied to multi-colour surveys such as the forthcoming Pan-STARRS surveys. The scope for cluster detection with ORCA is not limited solely to the optical regime. Preliminary tests with optical-IR band-merged catalogues show great promise, requiring minimal adaptation to facilitate the detection of the 4000Å break into the IR bands and beyond $z = 1$.

ACKNOWLEDGEMENTS

We thank the referee for their useful comments which improved the clarity of the paper. DNAM acknowledges an STFC PhD studentship, JEG and RGB thank the U.K. Science and Technology Facilities Council and the Natural Sciences and Engineering Research Council of Canada for financial support. The authors thank Alastair Edge, John Lucey, Kathy Romer, Ian Smail and John Stott for useful discussions, Carlton Baugh, Yan-Chuan Cai and Shaun Cole for access to the mock MDS lightcone data.

Calculations in portions of this work were performed on the ICC Cosmology Machine, which is part of the DiRAC Facility jointly funded by STFC, the Large Facilities Capital Fund of BIS, and Durham University.

Funding for the SDSS and SDSS-II has been provided by the Alfred P. Sloan Foundation, the Participating Institutions, the National Science Foundation, the U.S. Department of Energy, the National Aeronautics and Space Administration, the Japanese Monbukagakusho, the Max Planck Society, and the Higher Ed-

Figure 15. The purity of ΛCDM clusters detected by the ORCA algorithm. Low values indicate where clusters have included a large number of contaminating galaxies not belonging to the halo.
ucation Funding Council for England. The SDSS Web Site is http://www.sdss.org/.

The SDSS is managed by the Astrophysical Research Consortium for the Participating Institutions. The Participating Institutions are the American Museum of Natural History, Astrophysical Institute Potsdam, University of Basel, University of Cambridge, Case Western Reserve University, University of Chicago, Drexel University, Fermilab, the Institute for Advanced Study, the Japan Participation Group, Johns Hopkins University, the Joint Institute for Nuclear Astrophysics, the Kavli Institute for Particle Astrophysics and Cosmology, the Korean Scientist Group, the Chinese Academy of Sciences (LAMOST), Los Alamos National Laboratory, the Max-Planck-Institute for Astronomy (MPA), the Max-Planck-Institute for Astrophysics (MPA), New Mexico State University, Ohio State University, University of Pittsburgh, University of Portsmouth, Princeton University, the United States Naval Observatory, and the University of Washington.

REFERENCES

Abazajian K. N., Adelman-McCarthy J. K., Agüeros M. A., Allam S. S., Allende Prieto C., An D., Anderson K. S. J., Anderson, S. F et al., 2009, ApJS, 182, 543
Abell G. O., 1958, ApJS, 3, 211
Abell G. O., Corwin, Jr. H. G., Olowin R. P., 1989, ApJS, 70, 1
Allen S. W., Schmidt R. W., Fabian A. C., 2002, MNRAS, 334, L11
Balogh M. L., Navarro J. F., Morris S. L., 2000, ApJ, 540, 113
Barber C. B., Dobkin D. P., Huhndapua H., 1996, ACM TRANSACTIONS ON MATHEMATICAL SOFTWARE, 22, 469
Barkhouse W. A., Green P. J., Vikhlinin A., Kim D., Perley D., Cameron R., Silverman J., Mossman A. et al., 2006, ApJ, 645, 955
Benson A. J., Bower R., 2010, MNRAS, 405, 1573
Blanton M. R., Hogg D. W., Bahcall N. A., Brinkmann J., Britton M., Connolly A. J., Csabai I., Fukugita, M. et al., 2003, ApJ, 592, 819
Böhringer H., Voges W., Huchra J. P., McLean B., Giacconi R., 1990, ApJ, 435
Bozonella M., Miralles J., Pelló R., 2000, A&A, 363, 476
Bower R. G., Benson A. J., Malbon R., Helly J. C., Frenk C. S., Baugh C. M., Cole S., Lacey C. G., 2000, MNRAS, 370, 645
Bower R. G., Lucey J. R., Ellis R. S., 1992, MNRAS, 254, 601
Broadwin M., Ruel J., Ade P. A. R., Aird K. A., Anderson K., Ashby M. L. N., Bautz M., Bazzar G. et al., 2010, ApJ, 721, 90
Cai Y., Angulo R. E., Baugh C. M., Cole S., Frenk C. S., Jenkins A., 2009, MNRAS, 395, 1185
Calzetti D., Armus L., Bohlin R. C., Kinney A. L., Kormneef J., Storchi-Bergmann T., 2000, ApJ, 533, 682
Carlberg R. G., Yee H. K. C., Ellingson E., Abraham R., Gravel P., Morris S., Pritchett C. J., 1996, ApJ, 462, 32
Carlstrom J. E., Holder G. P., Reese E. D., 2002, ARAA, 40, 643
Cavaliere A., Fusco-Femiano R., 1976, A&A, 49, 137
Clowe D., Bradac M., Gonzalez A. H., Markevitch M., Randall S. W., Jones C., Zaritsky D., 2006, ApJ, 648, L109
Colberg J. M., Krughoff K. S., Connolly A. J., 2005, MNRAS, 359, 272
Cole S., Lacey C. G., Baugh C. M., Frenk C. S., 2000, MNRAS, 319, 168
Collister A. A., Lahav O., 2004, PASP, 116, 345
Crawford C. S., Edge A. C., Fabian A. C., Allen S. W., Bohringer H., Ebeling H., McMahon R. G., Voges W., 1995, MNRAS, 274, 75
Croom S. M., Richards G. T., Shanks T., Boyle B. J., Sharp R. G., Bland-Hawthorn J., Bridges T., Brunner, R. J. et al., 2009, VizieR Online Data Catalog, 739, 20019
Csabai I., Budavári T., Connolly A. J., Szalay A. S., Györy Z., Benitez N., Annis J., Brinkmann, J. et al., 2003, AJ, 125, 580
Dalton G. B., Efstathiou G., Maddox S. J., Sutherland W. J., 1992, ApJ, 390, L1
Dietrich J. P., Erben T., Lamer G., Schneider P., Schweke A., Hartlap, J. et al., 2007, A&A, 470, 821
Doherty M., Tanaka M., De Breuck C., Ly C., Kodama T., Kurk J., Seymour N., Vernet, J. et al., 2010, A&A, 509, A83+
Drinkwater M. J., Jurek J. R., Blake C., Woods D., Pimbblet K. A., Glazebrook K., Sharp R., Pracy, M. B. et al., 2010, MNRAS, 401, 1429
Ebeling H., Edge A. C., Allen S. W., Crawford C. S., Fabian A. C., Huchra J. P., 2000, MNRAS, 318, 333
Ebeling H., Edge A. C., Bohringer H., Allen S. W., Crawford C. S., Fabian A. C., Voges W., Huchra J. P., 1998, MNRAS, 301, 881
Ebeling H., Wiedenmann G., 1993, Phys. Rev. E, 47, 704
Eke V. R., Baugh C. M., Cole S., Frenk C. S., Norberg P., Peacock J. A., Baldry I. K., Bland-Hawthorn, J. et al., 2004, MNRAS, 348, 866
Ei-Ad H., Piran T., da Costa L. N., 1996, ApJ, 462, L13+
Evrard A. E., 1997, MNRAS, 292, 289
Fedeli C., Moscardini L., Marende, S., 2009, MNRAS, 397, 1125
Font A. S., Bower R. G., McCarthy I. G., Benson A. J., Frenk C. S., Helly J. C., Lacey C. G., Baugh, C. M. et al., 2008, MNRAS, 389, 1619
Frenk C. S., White S. D. M., Efstathiou G., Davis M., 1990, ApJ, 351, 10
Geach J. E., Murphy D. N. A., Bower R. G., 2011, MNRAS, 413, 3059
Gladders M. D., Lopez-Cruz O., Yee H. K. C., Kodama T., 2006, ApJ, 640, 157
Gladders M. D., Yee H. K. C., 2000, AJ, 120, 2148

—, 2005, ApJS, 157, 1
Goto T., Sekiguchi M., Nichol R. C., Bahcall N. A., Kim R. S. J., Annis J., Ivezic Z., Brinkmann, J. et al., 2002, AJ, 123, 1807
Gunn J. E., Carr M., Rockosi C., Sekiguchi M., Berry K., Elms B., de Haas E., Ivezic Z et al., 1998, AJ, 116, 3040
Hao J., Koester B. P., Mckay T. A., Rykoff E. S., Rozo E., Evrard A., Annis J., Becker, M., 2009, ApJ, 702, 745
Hayashi M., Kodama T., Koyama Y., Tadaki K. I., Tanaka I., 2011, MNRAS, 778
Hilbert S., White S. D. M., 2010, MNRAS, 404, 486
Hincks A. D., Acquaviva V., Ade P. A. R., Aguirre P., Amiri M., Appel J. W., Barrientos L. F., Battistelli E. S. et al., 2010, ApJS, 191, 423
Icke V., van de Weygaert R., 1991, QJRAS, 32, 85
Ivezic Z., Tyson J. A., Allsman R., Andrew J., Angel R., Axelrod T., Barr J. D., for the LSST Collaboration, 2008, arXiv:astro-ph/0805.2366
Kaiser N., Aussel H., Burke B. E., Boesgaard, H. and Chambers K., Chun M. R., Heasley J. N., Hodapp, K. W. et al., 2002, Society of Photo-Optical Instrumentation Engineers (SPIE) Conference Series, 4836, 154
Katgert P., Mazure A., den Hartog R., Adami C., Biviano A., Perea J., 1998, A&AS, 129, 399

ORCA
Figure 16. Stripe 82 cluster MGB J234341+00180.3 is an extended system detected between two maxBCG clusters (BCG J234322+00190.6 and BCG J234403+00130.6). For clarity, we have not plotted the Voronoi grid, but the cluster members are marked with blue cross-hairs. The maxBCG clusters are shown in red, with the central positions noted by the two smaller circles, and the larger circles corresponding to radii of $1h^{-1}\text{Mpc}$ based on the photometrically-estimated cluster redshift from Koester et al. [2007a].
Figure 17. Stripe 82 cluster MGB J234105+00180.3: an ORCA detection between two maxBCG clusters and on top of an X-ray cluster position. Members and their Voronoi cells are marked in blue, the thick circle indicating the estimated cluster centre. Grey dashed circles are associate cluster members arising from multiple detections of this cluster. Red data indicate the location of maxBCG clusters BCG J234122+00190.0 and BCG J234106+00120.4, with larger circles indicating a $1h^{-1}\text{Mpc}$ radius, smaller circles the BCG positions. Yellow data indicate the NORAS X-ray cluster RXC J2341.1+0018; the half-length of the large square corresponds to $1h^{-1}\text{Mpc}$ based on the cluster redshift, the small square noting the X-ray position, uncertain to approximately 1'. The X-ray-ORCA centroid separation is approximately 0.4'.