In Pursuit of LSST Science Requirements: A Comparison of Photometry Algorithms

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ABSTRACT. We have developed an end-to-end photometric data-processing pipeline to compare current photometric algorithms commonly used on ground-based imaging data. This test bed is exceedingly adaptable and enables us to perform many research and development tasks, including image subtraction and co-addition, object detection and measurements, the production of photometric catalogs, and the creation and stocking of database tables with time-series information. This testing has been undertaken to evaluate existing photometry algorithms for consideration by a next-generation image-processing pipeline for the Large Synoptic Survey Telescope (LSST). We outline the results of our tests for four packages: the Sloan Digital Sky Survey’s Photo package, DAOPHOT and ALLFRAME, DOPHOT, and two versions of Source Extractor (SExtractor). The ability of these algorithms to perform point-source photometry, astrometry, shape measurements, and star-galaxy separation and to measure objects at low signal-to-noise ratio is quantified. We also perform a detailed crowded-field comparison of DAOPHOT and ALLFRAME, and profile the speed and memory requirements in detail for SExtractor. We find that both DAOPHOT and Photo are able to perform aperture photometry to high enough precision to meet LSST’s science requirements, and less adequately at PSF-fitting photometry. Photo performs the best at simultaneous point- and extended-source shape and brightness measurements. SExtractor is the fastest algorithm, and recent upgrades in the software yield high-quality centroid and shape measurements with little bias toward faint magnitudes. ALLFRAME yields the best photometric results in crowded fields.

Online material: color figures, extended tables

1. INTRODUCTION

The next generation of astronomical surveys will provide data rates and volumes that dwarf those of current time-domain surveys (e.g., Tyson 2006; Kaiser 2006), requiring commensurate advances in astronomical image processing and data management capabilities. These surveys will enable synoptic study of such diverse science aspects as the minor planets of the solar system (Jones et al. 2006), Galactic structure through color-magnitude (Juric et al. 2005) and proper-motion (Munn et al. 2004) studies, time-domain variability (Becker et al. 2004), and the study of cosmological dark matter and dark energy using Type Ia supernovae (Wood-Vasey et al. 2007), baryon acoustic oscillations (Eisenstein et al. 2005), galaxy clustering (Bahcall et al. 2004), and weak lensing (Zhan 2006). These science goals require precision astrometric and photometric measurements of both stars and galaxies. The engineering challenge in these surveys is to design and manufacture a system able to obtain data of the requisite quality. The data management challenge is to reliably and rapidly transfer, analyze, and store the raw data and data products, with the algorithmic engineering challenge to realize the science goals through precision analysis of the data.

The Science Requirements Document (SRD) for the Large Synoptic Survey Telescope (LSST)1 includes constraints on point-source photometry and astrometry, as well as on stellar and galaxy shape measurements. These requirements are not to be violated in data or in software. The goal of this research is to test the latter, given a large set of input data. In particular, the LSST SRD requires that the root mean square (rms) of the unresolved source magnitude distribution around the mean value not exceed 0.005 mag in the $g$, $r$, and $i$ passbands, when supported by photon statistics. The measured photometric errors shall not exceed the quoted photometric errors by 10%. The rms of the distance distribution for stellar pairs with separations of 5', 20', and 200' shall not exceed 10, 10, and 15 mas in the $g$, $r$, and $i$ bands, respectively. Finally, for fields within 10° of zenith, the $r$- and $i$-band point-source ellipticity distribution will have a median value of no more than 0.04 and must be correctable to a distribution with a median no larger than 0.002.

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3 See http://www.lsst.org/.
Here we compare extant software packages in the context of these LSST science requirements. This includes DAOPHOT (Stetson 1987), DOPHOT (Schechter et al. 1993), ALLFRAME (Stetson 1994), SExtractor (Bertin & Arnouts 1996), and Photo (Lupton et al. 2002). We have established quality assessment metrics for comparing ensemble measurements of stellar positions, shapes, and brightnesses. Important algorithmic steps required to achieve this are the separation of stars and galaxies and the deblending of neighboring objects. Because the absolute “truth” is not known here, these comparisons are by necessity relative. We compare the times required to reduce astronomical images, as well as memory consumption, when possible.

While we have attempted to tune each package to obtain the best results for the ensemble of data, it is very likely that better results would emerge through individual study of each image. As such, this analysis reflects the results for a typical pipeline application of each package.

We summarize the requirements for characterizing stellar and extended sources in astronomical images in § 2. We describe the data used in the analysis in § 3, and our pipeline infrastructure in § 4 and summarize the algorithms that we tested in § 5. Our time-series database is outlined in § 6, and the algorithms used to “cluster” single detections into multiple measurements of astronomical objects are described in § 7. We discuss the methods used to select objects from our database in § 8. We describe the results of our analyses regarding star-galaxy separation, photometry, shape measurements, centroiding, and photometric depth in § 10–13. We focus on a crowded-field analysis of globular cluster M2 in § 14 and on algorithm timing and scaling tests in § 15. We conclude with an overall summary in § 16.

2. SOURCE MEASUREMENTS IN ASTRONOMY

The problem of point-source photometry is a well-studied one, with various solutions whose algorithms differ in their methods and implementation (e.g., Howell 1989; Thomson et al. 1992; Handler 2003; Ivezic et al. 2004; Pinheiro da Silva et al. 2006). The problem requires the correct modeling of an image’s point-spread function (PSF), the transfer function of point sources such as the atmosphere and the optics of the telescope. This solution typically includes an analytic model and an “aperture correction” that compensates for the limitations of the model (e.g., Tanvir et al. 1995; Handler 2003; Kuijken 2006).

In practice, the aperture and PSF fluxes are determined in a small aperture that is a small multiple of the PSF full width at half-maximum (FWHM). The aperture flux is an unweighted measurement, while the PSF flux is derived using the PSF as the weight. The aperture fluxes of bright stars are next measured out to a very large radius, where one is reasonably certain that all the light has been collected. The ratio of the bright-star flux in the large and small apertures yields a multiplicative flux correction to the small-aperture measurements. In general, these aperture corrections need to vary across an astronomical image because of spatial variation in the PSF. For very bright stars, aperture photometry yields a more accurate measurement of the flux than PSF photometry, due to limitations of the analytic model. However, for faint stars near the sky limit, PSF photometry yields a more precise measurement of the flux, since aperture photometry includes many contributions from sky pixels.

Galaxy photometry is much less studied, with a variety of pitfalls. Because of color changes in a galaxy’s light profile, the correct aperture to use before becoming sky-noise dominated is a function of the passband in which one is observing. Galaxies are also irregular in shape and may be deblended nonuniquely (Kushner et al. 2006). Typically, a basic symmetric model (de Vaucouleurs, exponential) is fitted to the light profile. For weak-lensing science, which requires precision measurement of the shapes of galaxies (e.g., Bernstein & Jarvis 2002), adaptive second moments of the light profile are used to quantify the ellipticity of galaxies. Photometric redshift measurements require the consistent accounting of flux in a variety of passbands and thus ideally require a simultaneous ensemble measurement of images taken through different filters (Collister et al. 2007).

3. THE DATA

One of the algorithms under study is the photometric reduction pipeline used by the Sloan Digital Sky Survey (SDSS): Photo. Photo is one of the few packages, and the only one analyzed here, that consistently performs both stellar PSF and extended-source photometry, and it represents a solid precursor pipeline for future surveys. However, Photo has been designed to operate solely on data from SDSS; testing of this algorithm requires that we operate on data from SDSS.

SDSS uses a dedicated 2.5 m telescope (Gunn et al. 2006) to provide simultaneous five-band imaging in u, g, r, i, z (Fukugita et al. 1996). The imaging camera contains 30 photometric CCDs arranged in six columns (Gunn et al. 1998). The images are obtained in drift-scan mode, and “fields” are defined corresponding to a scan length of 9′ (36 s of drift-scanning), with a field width of 14′. The five images corresponding to a given field, obtained in the order r-i-u-z-g, are simultaneously processed by Photo.

We have chosen to use data from two photometric runs of SDSS equatorial Strip 82N for these comparisons. These are runs 3437 (obtained MJD 52,578) and 4207 (MJD 52,936). The data for run 3437 are in the range 31°< R.A. < 23° (J2000.0), with median g-, r-, and i-band PSF FWHMs of 1.3", 1.1", and 1.1", respectively, and a median r-band sky brightness of 20.8 mag arc sec \(^{-2}\). The data for run 4207 are in the range 305°< R.A. < 60° (J2000.0), have a median seeing of 1.4", 1.3", and 1.2" in the g-, r-, and i-band data, and median sky brightness of r = 20.7 mag arc sec \(^{-2}\). There are approximately 27k objects per square degree detected by Photo in these images.

Because Photo determines the PSF model for a given image by using neighboring images (along the direction of the scan),
the other algorithms would be at a disadvantage when trying to measure the PSF from a single frame. For this reason, we “stitch” together three images along the direction of the scan into a $14' \times 27''$ image, with the frame of interest being in the middle. The algorithms operate on the entire stitched frame, but we accept only photometry from the central section.

4. THE ANALYSIS PIPELINE

To control the application of each algorithm to the data, we require a form of middleware that records progress and distributes jobs. For this we have chosen to use the Photpipe software developed by the SuperMACHO and ESSENCE collaborations (Smith et al. 2002).

The majority of Photpipe is written in the Perl language. This provides the internal glue that strings together the various processing steps. In general, the image-level computations are written in the C language. These applications are called by the Perl scripts.

As a programmatic summary, the Photpipe pipeline consists of a series of stages, each of which has actions that it undertakes, as well as dependencies on the successful completion of previous stages. By default, an ensemble of images is passed from stage to stage using input and output lists. We have added a stage for DAOPHOT, DOPHOT, and SExtractor, whose actions are merely to reduce each image using the algorithm. Results of the analysis are ingested into our time-series database (§ 6).

We made an effort to explore the response of DAOPHOT, DOPHOT, and SExtractor to different input parameters. However, because of the number of degrees of freedom available to each (on the order of 100 for both DOPHOT and SExtractor; on the order of 10 for DAOPHOT and 60 for the Perl-language scripts that control its application), it was infeasible to find which combination of parameters yielded the optimal results for every analysis presented here. We did vary the obvious tuning parameters, such as the input FWHM and significance threshold for object detection, degree of variation and complexity in the PSF model, and clustering size for matching up the ensemble of detections, ingesting the results of each analysis into our database as a separate data set. In total we ingested 112 permutations of dataset, algorithm, and algorithm input parameters, and we report here on those results that reflect our best pipelined application of each algorithm.

5. THE ALGORITHMS

In the following sections, we briefly summarize the photometry algorithms used in this analysis: Photo, DAOPHOT and ALLFRAME, DOPHOT, and two versions of SExtractor. More complete descriptions of each algorithm are given in the Appendix of Becker et al. (2007).

The SDSS photometric pipeline Photo contains a complete suite of data reduction tools that take the raw data stream, apply reduction and calibration stages, and extract photometry from the calibrated images. Because the images that we are using have been preprocessed by Photo, we expect that Photo has a distinct advantage in the quality of its photometric measurements. The SDSS imaging PSF is modeled heuristically in each band using a Karhunen-Loeve transform. Objects are measured self-consistently across all bands, and their positions and brightnesses are fit using a variety of models, including PSF and extended-source models.

The DAOPHOT package contains a set of algorithms primarily designed to do stellar photometry and astrometry in crowded fields. The tools are included as either subroutines in the executable program daophot or as independent executable programs. DAOPHOT builds its PSF using multiple iterations of source detection, PSF modeling, and source subtraction. The PSF model includes an analytic form, as well as a lookup table of corrections. While DAOPHOT operates on single images, ALLFRAME performs simultaneous measurements of all sources from a stack of images. DAOPHOT does not attempt to fully characterize extended sources. We designed a set of Perl-language scripts to automate the application of the DAOPHOT package. While the scripts have proven to be robust in the iterative building of PSFs (Becker 2000), they are also relatively slow. A significant fraction of the computing time spent running DAOPHOT is due to this implementation choice and not necessarily intrinsic to the DAOPHOT source code.

The DOPHOT package is designed to robustly produce a catalog of stellar positions, magnitudes, and star or galaxy classifications for detections from astronomical images. DOPHOT was designed to work on a large number of images quickly with little to no interaction with the user. However, the version of DOPHOT tested here is not the original software implementation but instead a version that has been extensively modified to operate robustly in the Photpipe environment. DOPHOT uses a single PSF model that is not allowed to vary spatially, in contrast to Photo and DAOPHOT, whose PSF models are allowed to vary across the image.

SExtractor is designed to quickly produce reliable aperture photometry catalogs on a large number of astronomical sources. SExtractor has been used to produce object catalogs for a variety of astronomical imaging surveys to date such as the NOAO Deep Wide-Field Survey (Jannuzi & Dey 1999), Team Keck Survey Great Observatories Origins Deep Survey (TKS-GOODS)-N Survey (Hook et al. 2002), Deep Lens Survey (Tyson et al. 2001), Infrared Array Camera (IRAC) Shallow Survey (Eisenhardt et al. 2004), and the Multimission Archive at STScI (MAST) Survey (Imhoff et al. 1999). Aside from the ease of installation, SExtractor is also notable for its speed and versatility. It is one of the few packages that aspires to distinguish and photometer both stars and galaxies, although its lack of a PSF model limits the accuracy of faint point-source photometry. Newer versions of the software include adaptive windowing functions to provide more accurate centroids and shapes than the default (isophotal) measurements.
6. THE DATABASE

To enable the following analysis, we installed a MYSQL client and server on our local computers and constructed a database to store our test results (both science and performance benchmarking).

We developed a variety of Python-language scripts to help properly ingest data (e.g., pipeline versions, parameter files, file locations) into the database in an organized manner. We ingested metadata on over 1000 SDSS images processed through Photo in five colors ($u$, $g$, $r$, $i$, and $z$) resulting in over 10 million detections in our Objects table. The main tables of our database are “Image,” “Objects,” and “algRun.”

1. Image: Metadata about images including data source (e.g. SDSS), date, exposure time, filter, and a pointer to world coordinate system information for the image.

2. Object: Data for sources (detections from an image) and objects (clusters of sources), including position ($x$, $y$ and right ascension-declination), classification, and various measures of intensity. In addition, sources are linked to the image on which they were detected.

3. algRun: Information about a particular run of a component, including the input parameters used for that run. All told, 112 instances of pipeline runs were ingested into the database, representing different combinations of input data, photometry algorithm, and input parameters. Both the Object and Image tables link to the algRun table.

7. CLUSTERING OF SOURCES INTO OBJECTS

After ingesting sources and images into the database, we require a method to associate sources into objects. This allows us to collate the $u$, $g$, $r$, $i$, and $z$ data for a single astronomical object, as well as to match up the reductions from different algorithms or from different nights. We use the OPTICS algorithm to do this clustering.

The OPTICS algorithm (ordering points to identify the clustering structure; Ankerst et al. 1999) is a density-based method to identify clusters of points in databases. In this ordering, a “reachability distance” is defined between neighboring points. When this distance is exceeded for neighboring points, the boundary of a cluster is defined. OPTICS is an improvement of the DBSCAN algorithm (Ester et al. 1996).

The user provides a minimum number of points to define the cluster core. In our case, for a given object we have four algorithms operating on five filters and two nights of data, meaning we ideally expect 40 points in a cluster. We run OPTICS requiring a minimum of five points to include objects missed in some filters due to their color, missed on some nights due to different image depths, or missed in different algorithms due to the vagaries of the software. Since we only have three algorithms other than Photo running on these data, an artifact in one image and in one filter should not lead to a spurious cluster. We do, however, find spurious clusters in the wings of bright stars, where multiple algorithms may detect signal in multiple passbands on multiple nights.

The user also defines reachability distance $\epsilon$ for a given core set of points. For all points in this neighborhood, all points within $\epsilon$ of it are searched, repeating until no more points can be added to the cluster. The data are stored in a tree-based spatial index. A search in the neighborhood $\epsilon$ of a given object scales with the number of points $N$ as $N \log N$. We chose a clustering distance of 1 pixel (0.4″).

One way that we found to optimize the clustering was to relate the size of each page in the database to the length of the input list to be clustered. We found that too large (or too small) a page size would impact the computation of the clustering by an order of magnitude. Figure 1 demonstrates the OPTICS run time as a function of the number of points per page (or “leaf”) in the database.

8. METHODOLOGY

In this section and those that follow, we describe the practical methods used to quantify DAOPHOT, DOPHOT, Photo, and SExtractor.

Our analyses are designed to ascertain the level of systematics inherent to each photometry algorithm by comparing the measured properties of objects on multiple nights. We also compare brightness, shape, and centroiding measurements by the different algorithms on the same imaging data. We start with the assumption that Photo’s star-galaxy classification is “truth” and use this information to derive similar classification boundaries for the other algorithms. We then repeat our analyses using these new algorithm-derived boundaries.

![Fig. 1](https://example.com/fig1.png)

**Fig. 1.**—Run time for clustering 2.4 million points as a function of leaf size in the internal lean-tree database used by OPTICS. Note the y-axis in units of $10^4$ s. See the electronic edition of the PASP for a color version of this figure.
Our initial queries to the Object table select all objects from the comparison algorithms, but only a subset of detections from Photo. We only include Photo detections where the obj_flags suggest that they were not saturated, blended, or bright, were found in the BINNED1 image, and were not deblended_as_moving. These objects essentially serve as the “seed” objects that we use for clustering.

We start this process by selecting only clusters where Photo has detections in both runs that it thinks are stars. This criterion is used to select measurements from other algorithms to be used for magnitude zero pointing, determination of star-selection criteria, and comparison of shape measurements and photometric depth. We use PSF magnitudes when available and aperture magnitudes otherwise.

DAOPHOT, DOPHOT, and SExtractor report their results in instrumental magnitudes, and we have to derive zero-point offsets if we want to directly compare their data to Photo. For each algorithm, filter, and run combination, we take all Photo-selected stars and find the $3\sigma$ clipped average difference in magnitudes between Photo and the algorithm (we use aperture magnitudes for SExtractor; PSF magnitudes for DAOPHOT and DOPHOT).

### 9. STAR/GALAXY SEPARATION

The initial step in this analysis is to define star-galaxy boundaries for each algorithm. To do this, we select all objects that Photo classifies as stars and galaxies and plot the distribution of the star-galaxy separation metrics from each algorithm. In particular, we have chosen to use sharp for DAOPHOT, type for DOPHOT, and class_star for SExtractor. By studying the distribution of these parameters, we can derive star-galaxy classification schemes for each algorithm. For all Photo-selected stars and galaxies, we plot each algorithm’s star-galaxy parameter in four magnitude bins: $14 < r < 20$, $20 < r < 20.5$, $20.5 < r < 21$, and $21 < r < 22$. Each window contains a histogram and the cumulative distribution of that parameter plotted as a dashed line. We show example results for DAOPHOT in Figure 2 and SExtractor in Figure 3.

#### 9.1. Results Using Photo’s Classification

In DAOPHOT, sharp for stars is distributed in a near Gaussian that is centered on value 0.0 with a characteristic width. Figure 2 shows the $r$-band distribution from run 4207. The data are split into four magnitude bins. The distribution for stars is plotted in the left panel; for galaxies, on the right. As expected, the width of the stellar sharp distribution widens as one proceeds to fainter objects, from 0.04 at the bright end to 0.17 at the faint end. The parameter distribution for galaxies remains relatively constant with magnitude. We have combined the analyses from runs 3437 and 4207 and calculated the width of the stellar distribution in the brightest bin. The mean and width of this distribution are listed in Table 1. We define our filter-dependent DAOPHOT star selection criterion as anything having sharp within $3\sigma$ of the mean in the brightest bin. We define galaxies as those objects with sharp larger than $+3\sigma$ from the mean. Anything with sharp less than $-3\sigma$ from the mean is sharper than the PSF and likely to be an image artifact. We note that

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4 See http://www.sdss.org/dr5/products/catalogs/flags.html.

5 Aperture photometry is performed at a radius of 7.4″.
other selection criteria are possible and may lead to better results, such as using parameters $\text{sharp}$ and $\text{chi}$ in combination. However, $\text{sharp}$’s highly symmetric distribution for stars and highly skewed distribution for galaxies in Figure 2 suggests that it is appropriate, although not necessarily optimal, to use it as the sole criterion. The same is true for the other metrics defined below.

DOPHOT returns a $\text{type}$ parameter for each object that it measures. A $\text{type} = 1$ object is considered a “perfect” star and is used in the computation of the weighted PSF. A $\text{type} = 3$ object is not as peaked as a single star and is assumed to be a blend. It is, however, photometered with a single PSF. A $\text{type} = 7$ object is too faint to do a full seven-parameter fit, so a four-parameter fit was undertaken. We found that stars in our data had almost exclusively $\text{type} = 1$, with very few having $\text{type} = 7$. We found that galaxies tended to have $\text{type} = 3$ or $\text{type} = 1$, with a small fraction of $\text{type} = 7$. Since this is our only selection criterion, we select stars as all objects with $\text{type} = 1$ and galaxies as all objects with $\text{type} = 3$, recognizing that our stars will have nonzero contamination by galaxies.

In SExtractor, $\text{class\_star}$ is designed to be a star-galaxy classification toggle, where a value of 1 represents an object highly likely to be a star. This requires that the correct input FWHM be applied for the filtering to work optimally. Therefore, we use the FWHM as derived by Photo as inputs to SExtractor. As Figure 3 shows, this parameter tends to work well. The top panel shows the distribution for stars, and the bottom for galaxies. For all filters except for $u$ band, we chose a cutoff of $\text{class\_star} = 0.8$ as the line separating stars from galaxies. In the $u$ band, many of the stars are also distributed near $\text{class\_star} = 0$, and we lowered our delineation to $\text{class\_star} = 0.2$.

The extent of galaxy contamination in these algorithms is summarized in Tables 2 and 3. We list in Table 2 the total fraction of objects that were classified as stars by both the algorithm and Photo (S-S), as stars in the algorithm and galaxies in Photo (S-G), as galaxies in the algorithm and stars in Photo (G-S), and galaxies in both algorithms (G-G). We make a similar comparison in Table 3, which lists the fraction of all objects that each algorithm (mis)classified in both runs. We limit this selection to objects brighter than 21st magnitude, where Photo’s star-galaxy...

**TABLE 1**

| Filter | Mean | rms |
|--------|------|-----|
| $u$    | 0.004| 0.096|
| $g$    | 0.001| 0.062|
| $r$    | 0.000| 0.043|
| $i$    | 0.003| 0.045|
| $z$    | 0.003| 0.081|

Notes.—Distribution of DOPHOT $\text{sharp}$ parameters for objects classified by Photo as stars. We find these distributions by combining all data from runs 3437 and 4207. These numbers were derived from the $3\sigma$ clipped distribution of sharpness parameters for all DOPHOT measurements that were clustered with objects Photo classified as stars between $r = 14$th and $r = 20$th magnitude. DOPHOT-selected stars are subsequently defined as anything having a sharpness within $\pm 3$ rms of the mean. DOPHOT-selected galaxies are objects with a sharpness larger than $+3$ rms of the mean; objects with sharpness smaller than $-3$ rms of the mean are likely cosmic rays or other defects.
separation has been tested extensively and is considered truth for the purposes of these comparisons.

From Table 2, we see that DOPHOT and Photo disagree on anywhere from 1% to 10% of all bright objects (increasing to \( \sim 20\% \) when looking at all brightnesses). In general, DOPHOT is more likely to classify something as a star that Photo thinks is a galaxy. The fraction of detected Photo-classified galaxies is also lowest in DOPHOT, suggesting that this algorithm is very inefficient at detecting galaxies, and biased toward classifying galaxies that it does find as stars. SExtractor tends to disagree with Photo in the opposite sense—SExtractor is likely to call something a galaxy that Photo classifies as a star. Run 3437 is particularly egregious in this regard. The most obvious cause is that we fed the wrong initial estimate of the stellar FWHM (derived from the Photo analysis) to the package, and it was therefore making poorly informed choices for star-galaxy separation. However, runs 3437 and 4207 were treated equally in this regard, so this is likely not the culprit.

DAOPHOT agrees with Photo a large fraction of the time and is slightly more likely to call a Photo-classified star a galaxy than a Photo-classified galaxy a star. We have created plots such as Figure 4 to investigate each permutation of (mis)classification. These depict color-color diagrams of objects classified in \( g, r, \) and \( i \) as either stars or galaxies. We plot here only the bright objects (\( 14 < r < 20 \)) classified by both DAOPHOT and Photo in run 3437 (the figure for run 4207 is very similar). To yield a point on this diagram, the object must be classified the same by each algorithm in all three passbands. Thus, the fraction of objects in each window will slightly disagree with the entries in Table 2. It is clear that the misclassifications (the off-diagonal

### Table 2

| Algorithm   | Run | Filter | S-S | S-G | G-S | G-G |
|-------------|-----|--------|-----|-----|-----|-----|
| DAOPHOT     | 3437| \( g \) | 0.93| 0.01| 0.02| 0.04|
|             |     | \( r \) | 0.82| 0.01| 0.05| 0.12|
|             |     | \( i \) | 0.81| 0.01| 0.05| 0.13|
|             | 4207| \( g \) | 0.95| 0.01| 0.01| 0.03|
|             |     | \( r \) | 0.87| 0.01| 0.02| 0.09|
|             |     | \( i \) | 0.85| 0.02| 0.03| 0.10|
| DOPHOT      | 3437| \( g \) | 0.93| 0.04| 0.00| 0.03|
|             |     | \( r \) | 0.87| 0.07| 0.00| 0.05|
|             |     | \( i \) | 0.83| 0.13| 0.00| 0.04|
|             | 4207| \( g \) | 0.96| 0.01| 0.00| 0.03|
|             |     | \( r \) | 0.91| 0.05| 0.00| 0.04|
|             |     | \( i \) | 0.87| 0.09| 0.00| 0.03|
| SExtractor  | 3437| \( g \) | 0.35| 0.00| 0.59| 0.06|
|             |     | \( r \) | 0.57| 0.00| 0.28| 0.15|
|             |     | \( i \) | 0.56| 0.00| 0.25| 0.18|
|             | 4207| \( g \) | 0.90| 0.00| 0.05| 0.05|
|             |     | \( r \) | 0.83| 0.01| 0.02| 0.14|
|             |     | \( i \) | 0.74| 0.01| 0.09| 0.16|

**Notes.**—The fraction of total clustered objects brighter than 21st magnitude classified by the algorithm and Photo as a star (S-S), classified by the algorithm as a star and Photo as a galaxy (S-G), classified by the algorithm as a galaxy and Photo as a star (G-S), and classified by both the algorithm and Photo as a galaxy (G-G). This table indicates the degree of agreement between algorithms for a given set of data.

### Table 3

| Algorithm   | Filter | S-S | S-G | G-S | G-G |
|-------------|--------|-----|-----|-----|-----|
| DAOPHOT     | 3437   |     | 0.57| 0.00| 0.28| 0.15|
|             | 4207   | \( g \) | 0.90| 0.00| 0.05| 0.05|
|             |       | \( r \) | 0.83| 0.01| 0.02| 0.14|
|             |       | \( i \) | 0.74| 0.01| 0.09| 0.16|
| DOPHOT      | 3437   |     | 0.90| 0.00| 0.05| 0.05|
|             | 4207   | \( g \) | 0.90| 0.00| 0.05| 0.05|
|             |       | \( r \) | 0.83| 0.01| 0.02| 0.14|
|             |       | \( i \) | 0.74| 0.01| 0.09| 0.16|

**Notes.**—The fraction of total clustered objects brighter than 21st magnitude classified by the algorithm in both runs as a star (S-S), classified as a star in run 4207 and galaxy in 3437 (S-G), classified as a galaxy in run 4207 and star in 3437 (G-S), and as a galaxy in both runs (G-G). This table indicates the degree of agreement within a given algorithm for a given set of objects.

![Fig. 4.](image_url)
plots) are drawn more from the stellar than the galactic locus; thus, we conclude that DAOPHOT correctly calls some objects stars that Photo incorrectly calls galaxies, and vice versa.

9.2. Results Using Each Algorithm’s Classification

We also investigate the consistency within a given algorithm by looking at the classifications of the same object detected in both runs. This is listed in Table 3. As discussed above, DOPHOT is biased toward calling objects stars but shows here that it is very self-consistent in that regard. SExtractor classifies a higher fraction of objects as galaxies than do the other algorithms and apparently had difficulty with objects classified as stars in 4207 and galaxies in 3437. DAOPHOT disagrees with itself for 12% of objects, while Photo is the most consistent (∼2%) with regards to misclassifications of these bright objects. We note that if we examine the entire sample of clustered objects, including objects fainter than 21st magnitude, the misclassification rates in Table 3 degrade worst for Photo, increasing from ∼2% to ∼12%. The ratios for the other algorithms tend to remain constant at fainter magnitudes.

9.3. Classification Conclusions

Both DOPHOT and SExtractor have inadequacies in their star-galaxy classification schemes as derived in this experiment. It is very likely that improvements can be made to SExtractor using the nonlinear filters from Enhance Your Extraction (EyE), and it should be carefully considered as an option with the potential to contribute to LSST algorithm development. Surprisingly, DAOPHOT does a better job at classification than these algorithms, although its galaxy characterization methods are limited. Photo is the best all-around package in this regard due to its extensive analysis and characterization of each object.

10. PHOTOMETRY

For Photo-selected stars and galaxies, we calculate the difference of an object’s magnitude as measured by algorithm $\text{alg}_1$ in run1 and $\text{alg}_1$ in run2, or by algorithm $\text{alg}_1$ in run1 and algorithm $\text{alg}_2$ in run1. We plot these distributions as a function of magnitude. We do this for both aperture and PSF (when available) magnitudes, and for stars and galaxies. Example $r$-band results for DAOPHOT are shown in Figure 5 for both aperture and PSF photometry. Each figure contains four panels, described below.

10.1. Panel 1

The differences in measured magnitudes ($\Delta M = M_1 - M_2$) are plotted as a function of Photo’s magnitude. The median $\Delta M$ of objects brighter than 18th magnitude (or the brightest magnitude plus 1 if no objects brighter than 18th are present; typically this uses thousands of objects) was subtracted off of the entire distribution, so that it is centered on $y = 0$. We cut out the brightest and dimmest 0.5% of the data to avoid outliers. At the bright end, the width stops following Poisson statistics and levels off at a characteristic width indicative of systematics in the analysis. It is this width that we choose to characterize our algorithms.

For aperture magnitudes, the systematic floor is smaller at the bright end because there is no reliance on any PSF model, and

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Fig. 5.—Figure described in § 12 for DAOPHOT’s $r$-band photometry of stars. Figure on the left is for aperture photometry, on the right is PSF photometry. See the electronic edition of the PASP for a color version of this figure.
aperture measurements are ideally Poisson limited. This distribution shows a characteristic broadening at fainter magnitudes as measurements become sky-noise dominated. We naively expected most algorithms to perform similarly well in aperture magnitude measurements. However, there are enough degrees of freedom in centroiding and in treating the brightness of neighboring objects that these results in actuality are significantly different.

For PSF magnitudes, the bright-end systematic floor is much larger due to reliance on a PSF model that is certain to be incomplete at some level. Ideally, gross errors in the PSF model come out in the aperture correction, and this systematic floor is then indicative of the degree of spatial variation in the aperture corrections. At fainter magnitudes, the distribution remains much tighter than for aperture measurements, since sky noise does not contribute as much in a PSF-weighted measurement.

10.2. Panel 2

We divide the $\Delta M$ distribution into 10 bins. The points in each bin are sorted by $\Delta M$ and the first (Q1) and third (Q3) quartile are determined (the indices corresponding to 0.25 and 0.75 the length of the sorted array, respectively). The value of the points associated with Q1 and Q3 are used to determine the interquartile range (IQR) of these data. We choose to use the IQR to lessen our sensitivity to outliers (such as variable stars).

We find the uncertainty in this width by assuming that the data are normally distributed, where $\sigma_{\text{mean}} = 0.74 \text{IQR}$ and $\sigma_{\text{median}} = (\pi/2)^{1/2} \sigma_{\text{mean}}$. The standard deviation in the IQR is $\sigma_{\text{IQR}} = \sqrt{\pi}0.55 \text{IQR}$. The uncertainty in the IQR is $\sigma_{\text{IQR}}/(N-1)^{1/2}$.

We plot $\sigma_{\text{mean}}$ and its uncertainty (as derived from the IQR) in each bin. These data are then fit with the functional form $A + B z + C z^2$, where $z = 10^{0.4 M}$, which describes well the growth of this envelope with magnitude. This best fit is plotted as a solid line. We evaluate this equation 1 mag below the brightest data point and use this single number to characterize the systematics inherent in the comparison. The 3 $\sigma$ envelope allowed by this relationship is plotted in panel 1. These results are summarized in Table 4 for Photo-selected stars.

We note that the LSST Science Requirement Document states that photometry should be reproducible to 0.005 mag. That translates into a systematic bin width at the bright end of $0.005\sqrt{2}$, or 0.007 mag.

10.3. Panel 3

We evaluate and plot the fraction of stars in panel 1 that are more than 3 $\sigma$ from the mean. For night-to-night comparisons, this is very sensitive to the level of variability in the sample. For algorithm-to-algorithm comparisons on a given set of data, it allows us to uncover differences in the algorithms.

10.4. Panel 4

We add in quadrature the uncertainties associated with each component M1 and M2 and plot the distribution of $\Delta M/\sigma_{\Delta M}$. These data are binned, and we derive each bin’s IQR and its uncertainty and overplot these points. If the photometry packages accurately quantify the measurement uncertainties, these binned points should all lie near 1.0.

10.5. Results Using Photo-Selected Stars

We have designed three variants of the tests described above to characterize the algorithms’ photometric performance: comparing photometry of data taken on different nights as an overall characterization of each algorithm; comparing different algorithms’ photometry of the same data, providing a relative characterization that is insensitive to stellar variability; and comparing aperture and PSF magnitudes from the same algorithm.

### Table 4

**Width of $\Delta M$ Distribution for Photo-Selected Stars**

| Algorithm       | Magnitude | u  | g  | r  | i  | z  |
|-----------------|-----------|----|----|----|----|----|
| DAOPHOT         | Aperture  | 0.27 | 0.006 | 0.006 | 0.007 | 0.015 |
|                 | PSF       | 0.032 | 0.018 | 0.018 | 0.017 | 0.017 |
| DOPHOT          | Aperture  | 0.024 | 0.009 | 0.008 | 0.008 | 0.011 |
|                 | PSF       | 0.031 | 0.026 | 0.031 | 0.037 | 0.031 |
| Photo           | Aperture  | 0.027 | **0.007** | **0.006** | **0.007** | 0.015 |
|                 | PSF       | 0.029 | 0.019 | 0.019 | 0.021 | 0.019 |
| SExtractor 2.3.2| Aperture  | 0.057 | 0.009 | 0.008 | 0.010 | 0.035 |
|                 | PSF       | ... | ... | ... | ... | ... |
| SExtractor 2.4.4| Aperture  | 0.057 | 0.009 | 0.008 | 0.010 | 0.035 |
|                 | PSF       | ... | ... | ... | ... | ... |

**Notes:** Characteristic widths of $\Delta M$, evaluated 1 mag below the brightest non-saturated object, representing the repeatability of photometric measurements of objects classified by Photo as stars, as described in § 10. Measurements compatible with LSST’s science requirements (0.007 mag) are highlighted in bold.
on the same data, yielding an estimate of the scatter introduced by spatial variation of the aperture corrections.

We first characterize the photometric accuracy of each algorithm by comparing the brightness of Photo-selected stars measured in both SDSS runs. Figure 5 shows example \( r \)-band summary plots for DAOPHOT in both aperture and PSF photometry for Photo-selected stars. The widths of the \( \Delta M \) distributions are summarized in Table 4. We note that both Photo and DAOPHOT produce \( g \), \( r \), and \( i \)-band aperture photometry that meets LSST’s SRD on photometric accuracy. No other algorithms are able to meet this requirement, failing to reach the benchmark of 0.007 mag. We note that no algorithms are able to meet the SRD in PSF photometry—the numbers consistently fall short by a factor of 2–3. DOPHOT performs worst in terms of PSF photometry.

Most algorithms tend to underestimate aperture magnitudes of bright objects compared to the empirical scatter, with the exception of Photo, which tends to overestimate the aperture errors of bright objects by as much as a factor of 2. SExtractor underestimates the aperture errors of all objects by a factor of 2–3. Photo’s PSF magnitude errors represent the empirical scatter very faithfully. DOPHOT and DAOPHOT underestimate their PSF error uncertainties by \( \sim 20\% \).

We next look at the width of the \( \Delta M \) distribution for different algorithms running on the exact same data. This is insensitive to stellar variability and allows us to localize any differences to the algorithms themselves. The results for the \( r \) band are listed in Tables 5 and 6 for PSF and aperture photometry, respectively. The aperture results are very similar for all pairs of algorithms, while the PSF-photometry comparison of Photo to DAOPHOT is superior to any comparison using DOPHOT.

Finally, we compare aperture and PSF magnitudes from the algorithms, yielding an estimate of the additional scatter coming from spatial variation in the aperture corrections (Table 7). We limit our comparison to Photo-selected stars. A priori, we expect Photo to outperform all other algorithms here because its PSF magnitudes have already been aperture corrected. Ideally, the scatter here should be very close to the aperture photometry results in Table 4. Table 7 indicates that Photo’s results are equivalent to DAOPHOT’s, and closer to the PSF-photometry scatter than the aperture photometry scatter. This suggests that Photo’s aperture corrections have not successfully accounted for spatial variation in the PSF. The numbers in Table 7 do tend to bridge the difference between the aperture and PSF scatter in Table 4, verifying that the PSF-photometry scatter contains a baseline contribution from the aperture photometry and an additional contribution from aperture corrections.

### 10.6. Results with Algorithm-Selected Stars

#### TABLE 7
**Width of \( \Delta M \) Distribution for Photo-selected Stars; PSF versus Aperture Magnitudes**

| Algorithm | Run | \( u \) | \( g \) | \( r \) | \( i \) | \( z \) |
|-----------|-----|--------|--------|--------|--------|--------|
| DAOPHOT   | 3437 | 0.021  | 0.013  | 0.013  | 0.016  | 0.021  |
|           | 4207 | 0.021  | 0.016  | 0.014  | 0.019  | 0.024  |
| DOPHOT    | 3437 | 0.022  | 0.018  | 0.024  | 0.028  | 0.030  |
|           | 4207 | 0.017  | 0.018  | 0.027  | 0.034  | 0.024  |
| Photo     | 3437 | 0.021  | 0.014  | 0.012  | 0.013  | 0.015  |
|           | 4207 | 0.020  | 0.017  | 0.014  | 0.015  | 0.018  |

**Notes.**—Characteristic widths representing the repeatability of photometric measurements of objects classified by Photo as stars, as described in § 10. This table compares aperture vs. PSF magnitudes and is primarily sensitive to spatial variations in the aperture corrections to PSF photometry.
We repeat this analysis using objects each algorithm selects as a star. These results are listed in Table 8, and are very similar to the Photo-selected analysis. The largest difference is that the fraction of $3\sigma$ outliers increases by a factor of 2–3, indicating that the star-galaxy classification schemes for the algorithms are inferior to Photo’s. Some fraction of this additional scatter comes from not knowing exactly which pixels in the images have been interpolated over by Photo due to cosmic rays or bad pixels.

10.7. Photometry Conclusions

The aperture and PSF photometry from DAOPHOT and Photo are clearly superior. In particular, DAOPHOT performed as well as Photo, which is encouraging, as Photo was designed and commissioned with this SDSS data set in mind.

No algorithms were able to meet the LSST SRD in terms of PSF photometry. The ideal aperture corrections to the PSF photometry should bring the PSF scatter in line with that from the aperture photometry. The only algorithm for which this degree of calibration has been done is Photo. However, it appears that Photo has not sufficiently compensated for spatial variations in its aperture corrections to PSF magnitudes because its aperture versus PSF scatter are commensurate with DAOPHOT’s.

As far as calculating uncertainties, the PSF magnitude errors from Photo most closely track the empirical uncertainties. Aperture photometry uncertainties are either over- or underestimated in all algorithms.

It is clear that the task of PSF photometry still requires significant research and development if LSST is to meet its SRD in terms of photometric accuracy.

11. SHAPE MEASUREMENTS

For the Photo-selected stars and galaxies, we extract the algorithm shape parameters $I_{xx}$, $I_{yy}$, and $I_{xy}$ (DAOPHOT does not report these values on an object-by-object basis). We calculate the ellipticities derived from these moments

$$e_1 = \frac{I_{xx} - I_{yy}}{I_{xx} + I_{yy}}; \quad e_2 = \frac{2I_{xy}}{I_{xx} + I_{yy}}; \quad (1)$$

and generate figures comparing each algorithm’s shape measurements to Photo’s, dividing the data into four magnitude bins. We plot a linear relationship between Photo’s shape and that from the algorithm. The rms of the scatter about this line is calculated and listed in Table 9 for Photo-selected stars and in Table 10 for Photo-selected galaxies. Figure 6 shows a representative set of figures comparing $r$-band Photo and SExtractor ellipticity parameters from run 3437.

11.1. Shape Measurement Results

SExtractor is the only algorithm that we tested that reliably calculates the shapes of galaxies, and thus we have limited our comparison of shape measurements to Photo and SExtractor. In addition, for ease of tabulation and interpretation, we present

| Ellipticity | Algorithm     | Run  | rms  | Intercept | Slope  |
|-------------|---------------|------|------|-----------|--------|
| e1          | SExtractor 2.3.2 | 3437 | 0.026| 0.020 | 0.406 |
| e2          | SExtractor 2.3.2 | 3437 | 0.021| −0.033 | 0.447 |
| e1          | SExtractor 2.3.2 | 4207 | 0.034| −0.051 | 0.393 |
| e2          | SExtractor 2.3.2 | 4207 | 0.030| 0.014 | 0.420 |
| e1          | SExtractor 2.4.4 | 3437 | 0.002| −0.003 | 2.046 |
| e2          | SExtractor 2.4.4 | 3437 | 0.001| −0.000 | 2.060 |
| e1          | SExtractor 2.4.4 | 4207 | 0.004| −0.016 | 2.141 |
| e2          | SExtractor 2.4.4 | 4207 | 0.002| 0.001 | 2.181 |

Notes.—Comparison of Photo and SExtractor $r$-band ellipticity measures for Photo-selected stars with $14 < r < 20$. We fit a line to the relationship and evaluate the rms perpendicular to the principal axis. SExtractor 2.3.2 uses “isophotal” shape measures, and SExtractor 2.4.4 “windowed” shape measures.
only the results of the $r$-band analyses. We note that the $g$- and $i$-band results are quantitatively similar.

We compare the ellipticities derived from both the “isophotal” shape measurements from SExtractor 2.3.2 and the “windowed” measurements from SExtractor 2.4.4. The linear relationships between Photo’s and SExtractor’s $r$-band measurements, in the form $e_{\text{Photo}} = A + B e_{\text{SExtractor}}$, are shown in Table 9 for stars and in Table 10 for galaxies. We report these numbers for the brightest magnitude bin ($14 < r < 20$). We also list the rms scatter about this line.

We first note the significantly reduced scatter from the best-fit linear relationships when using the “windowed” shape measurements from SExtractor 2.4.4. In particular, this yields up to 1 order of magnitude less scatter in the stellar shape measures (Table 9), suggesting that SExtractor 2.3.2 is not to be used for determining stellar shapes and ellipticities. The improvement for galaxies is a more modest factor of 3 (Table 10), but still very significant.

The ellipticities of galaxies in SExtractor 2.3.2 is similar to that in Photo (slope $\sim 1$); the ellipticities of both stars and galaxies in SExtractor 2.4.4 are different than in Photo (slope $\sim 2.0$ for stars, $\sim 1.8$ for galaxies). Figure 6 shows an example plot of ellipticity comparisons for Photo-selected galaxies. The left panel shows this relationship for SExtractor 2.3.2, and the right panel for SExtractor 2.4.4. The isophotal measurements clearly lead to a tighter relationship.

### 11.1.1. Shape Measurement Conclusions

Adaptive second moments are more reliable than isophotal moments. We recommend that all SExtractor analyses relying on shape measurements use “windowed” shape measures. Non-windowed shape measures should not be used for stars.

### 12. CENTROIDING

We also compare centroiding offsets between objects as measured in the same images by different algorithms. To do this accurately, we must first determine the conventions used to describe the image array. For both DAOPHOT and SExtractor, the center of the lower-left hand corner pixel (LLHC) is coordinate $(1.0, 1.0)$. In Photo and DOPHOT, the LLHC is at coordinate $(0.5, 0.5)$.

We perform an analysis similar to that described in § 10 but describe the distribution of pixel offsets as a function of magnitude. This should reveal any centroiding biases as a function of magnitude. Figure 7 includes the three panels described in § 10.1, § 10.2, and § 10.3. Here the width of the bright end of the distribution in the top panel of each figure reflects centroiding systematics.

![Fig. 6.—Comparison of run 3437 $r$-band galaxy ellipticity measurements in SExtractor and Photo. $e_1$ is plotted as green triangles, and $e_2$ as red squares. In each figure, the four panels are for data in different $r$-band magnitude bins, and compare the shape measured in SExtractor on the $x$-axis, and Photo on the $y$-axis. The left figure shows results from SExtractor 2.3.2 and the right figure SExtractor 2.4.4. The lines show the best fits given in Table 10, dashed for $e_1$ and solid for $e_2$.](image-url)
We also plot in each top panel a quadratic fit to the median value of the \( x, y \) coordinate pixel offsets of the form \( \Delta_{x,y} = A + Bz + Cz^2 \), where \( z = M - M_0 \), where \( M_0 \) is the magnitude of the first (brightest) bin and \( M \) the central magnitude for each bin. We plot the median values and their uncertainties, and the functional fit as a solid line. Any shape to this distribution \((B \neq C \neq 0)\) suggests systematics in object centroiding as a function of magnitude. These results are summarized in Table 11 for Photo-selected stars. Table 12 shows the width of this distribution, evaluated 1 mag below the brightest unsaturated star, comparing algorithm to algorithm for \( r \)-band centroids in run 3437 (upper triangular matrix) and run 4207 (lower triangular matrix).

12.1. Centroiding Results

We compare the measured positions of objects in each image as a function of magnitude. Accurate centroiding is required to deliver the SRD relative astrometry requirement of 0.01" (here 0.025 pixels). We are unable to comment on the absolute astrometry requirements, since that involves knowledge of astrometric distortions in the focal plane, which are different here than will be the case in LSST.

We list the results of the quadratic fit in Table 11 for Photo-selected stars. SExtractor 2.3.2 consistently has significant offsets, linear, and quadratic terms. DOPHOT rarely shows significant quadratic terms but tends to have significant zero-point offsets at \( \sim 0.01 \) pixels. Both DAOPHOT and SExtractor 2.4.4 compare very well with Photo’s positional measurements, routinely having offsets below 0.005 pixels, linear terms below 0.003 pixels \( \text{mag}^{-1} \), and quadratic terms below 0.001 pixels \( \text{mag}^{-2} \).

An example demonstrating the improvements between SExtractor 2.3.2 and SExtractor 2.4.4 is shown in Figure 7. Here we plot two figures containing the three panels described in § 12.

![Figure 7](image)

**TABLE 11**

| Algorithm | Run  | Filter | M0  | \( A_x \) | \( B_x \) | \( C_x \) | \( A_y \) | \( B_y \) | \( C_y \) |
|-----------|------|--------|-----|--------|--------|--------|--------|--------|--------|
| DAOPHOT ... | 3437 | u      | 16.41 | 0.000  | 0.002  | 0.000  | -0.001 | 0.000  | -0.000 |
|           |      | g      | 15.29 | 0.000  | -0.001 | 0.000  | -0.003 | 0.005  | -0.001 |
|           |      | r      | 14.79 | -0.000 | 0.000  | -0.000 | -0.005 | 0.004  | -0.001 |
|           |      | i      | 14.61 | -0.000 | 0.000  | -0.000 | -0.003 | 0.003  | -0.001 |
|           |      | z      | 14.44 | 0.003  | -0.003 | 0.000  | -0.001 | 0.002  | -0.000 |

**Notes.**—Results of the analysis described in § 12 for Photo-selected stars. Coefficients subscripted \( x \) are for the \( x \)-axis offsets, \( y \) are for the \( y \)-axis. This analysis tests systematics in centroiding as a function of magnitude. Table 11 is published in its entirety in the electronic edition of the PASP. A portion is shown here for guidance regarding its form and content.
The left panel shows the distribution of $z$-band $\Delta X$ pixel offsets between SExtractor 2.3.2 and Photo. The right panel provides a comparison between SExtractor 2.4.4 and Photo. It is clear there is a much smaller trend of the median pixel offset with magnitude in SExtractor 2.4.4, as well as a smaller overall rms to the distribution.

We use this rms at the bright end to further characterize the centroiding accuracy. This comparison of all algorithm centroids is shown in Table 12 for $r$-band $x$-coordinate centroids.

12.2. Centroiding Conclusions

The LSST SRD relative astrometry requirement of 0.01" (1/70 the median SRD $r$-band seeing of 0.7") is not likely to be violated in software. The windowed centroids of SExtractor 2.4.4 are comparable to the PSF centroids of DAOPHOT and PHOTO, and a significant improvement over SExtractor 2.3.2.

13. PHOTOMETRIC DEPTH

We select all clustered objects that have been classified as a star by each algorithm for each run and create star count histograms. We find the bin with the maximum number of stars found by each algorithm, as well as the cumulative fraction of the histogram as a function of magnitude. We characterize the photometric depth of each algorithm by determining the magnitude bins below which 95\% ($M_{95}$) and 99\% ($M_{99}$) of the objects have been detected. These values, as well as the peak of the functions, are listed in Table 13.

13.1. Photometric Depth Results

Using $M_{99}$ as a proxy for photometric depth, Photo is consistently deeper than DAOPHOT and DOPHOT in PSF magnitudes—in many cases significantly. We can trace this back to the...
definition of “significance” in the object detection stages. For example, DAOPHOT triggers off the central pixel of an object in the image convolved with its PSF, yielding a weighted sum of neighboring pixels. Photo does a similar smoothing, but also grows the source by an amount approximately equal to the radius of the seeing disk, and defines a source as a connected set of pixels that are detected in at least one of the five passbands. Unfortunately, it is not sufficient to merely lower DAOPHOT’s object detection threshold to compensate for these differences without also enacting a change in how the algorithm evaluates the notion of “significance.” By lowering the threshold we would be allowing an unacceptable number of artifacts through along with the fainter astronomical objects. The ideal object detection algorithm would trigger off medium significance pixels and determine the integrated significance of all neighboring (e.g., eight-connected) pixels, comparing the latter to the user-defined detection threshold.

The comparison between Photo and SExtractor is slightly more difficult, since aperture photometry is not the ideal measurement to use in star count comparisons. For example, the peaks of Photo’s aperture photometry star counts are frequently 2–3 mag fainter than for its PSF star counts. At least for the $g$ and $r$ passbands, the metric $M_{\text{ga}}$ is approximately the same for aperture and PSF photometry, so we use these filters in our SExtractor comparison. On both nights, SExtractor stops more than 1 mag brighter than Photo in $g$ and slightly less than 1 mag in $r$.

13.2. Photometric Depth Conclusions

It is difficult to compare photometric depths in the context of incomplete star/galaxy separation schemes. The star counts of all algorithms are contaminated to some degree by galaxies. However, because Photo measures and deblends stars and galaxies simultaneously, we believe that this yields the most accurate classification criteria and thus the most accurate star counts.

DAOPHOT is primarily designed to photometer stars, and while it does a reasonable job of agreeing with Photo on object classification (Table 3), it also is overcomplete compared to Photo for brighter objects, where Photo is known to do well, and is also incomplete for fainter objects. The former is likely due to detection of artifacts in the images, as well as misclassification of galaxies as stars.

14. ANALYSIS OF GLOBULAR CLUSTER M2

Globular cluster M2 (NGC 7089) is located in our imaging strip. This cluster contains approximately 150,000 stars, with a core radius of 0.34″. This is a highly concentrated structure that will test the limits of any photometric software tasked to analyze it. In fact, the majority of Photo’s attempts to reduce images containing this cluster are unsuccessful, failing at the stage of deblending.

We have chosen to use this particular field to test DAOPHOT’s and ALLFRAME’s abilities to do stellar photometry in crowded fields. With the vast majority of objects in these images being cluster stars, we expect minimal contamination from background galaxies. We do, however, expect to encounter problems with the brightest cluster stars (13th magnitude), which saturate in the standard SDSS exposures. In the images that we are using, saturated pixels and bleeds have been interpolated over by Photo, leaving the profiles of these objects inconsistent with the PSF. DAOPHOT is therefore inclined to consider these objects extended and will fit an ensemble of PSFs to the object until enough have been added to “vacuum” up all of its flux.

This analysis will also serve as a proxy for how close LSST can observe to the Galactic plane and still maintain a given level of photometric precision. However, in such crowded fields, aperture photometry is neigh impossible. In addition, as § 10 has shown, PSF photometry is unable to produce results with the required accuracy. It is unclear whether it is possible, even in the most idealized case, for the SRD requirements to be met in such crowded fields.

14.1. Photometry

Due to the degree of stellar crowding in this field, OPTICS clustering runs yielded marginal results with a clustering distance of 1 pixel (0.4″). This was characterized by large scatter when matching the centroids of objects in DAOPHOT and ALLFRAME, at the level of 0.8 pixel rms in the $r$ band. We instead chose to cluster the data with a half pixel (0.2″) clustering distance, which yielded much improved results (rms scatter of 0.04 pixel in the $r$ band). Clustering at a quarter pixel (0.1″) did not significantly alter the results.

The results for the $\Delta M$ distribution measurements are listed in Table 14. For both algorithms, we used the star-galaxy classification schemes derived from the previous analyses and described in Table 1.

The results of this analysis are very encouraging. We first note that the first two sets of data (DAOPHOT and ALLFRAME) in Table 14 correspond to objects classified by DAOPHOT as stars. To have clustered with DAOPHOT detections, this subset of the data will not reach as deep as the full ALLFRAME reductions. Therefore, these numbers do not directly reflect ALLFRAME’s photometry of faint objects but instead the fact that ALLFRAME is better able to deblend the stars used in this analysis from faint objects that were missed in DAOPHOT. The second set of ALLFRAME results are for objects classified by ALLFRAME as stars, and thus also probes the distribution of stars missed in DAOPHOT because they were too faint or blended. We emphasize that the PSFs used in the two analyses are exactly the same, and any improvements may be directly attributed to better deblending and centroiding.

The aperture photometry results are considerably worse here than as reflected in the sparse-field analysis described in Tables 4.
and 8. This is to be expected, as the field is extraordinarily crowded and there is a very steep and significant background sky gradient due to unresolved cluster stars. Both the $r$- and $i$-band aperture results are considerably worse than in the other passbands, in this case due to the extreme crowding conditions in these filters.

The PSF photometry shows a marked improvement over the aperture photometry results, particularly in the $r$- and $i$-band data where the images are most crowded. The $g$-band PSF photometry is the most problematic in the DAOPHOT reductions. However, the magnitude scatter for objects classified by DAOPHOT as stars is reduced by approximately 25% when going to the stacked analysis of ALLFRAME. In particular, the $g$-band photometry improves significantly, suggesting that DAOPHOT did a poor job of selecting all the stellar $g$-band objects, and a proper deblending was only possible by using constraints from the $r$- and $i$-band data. We also note that the ALLFRAME PSF-photometry results are commensurate with the sparse-field analyses described in Tables 4 and 8. This indicates that DAOPHOT + ALLFRAME is indeed a powerful combination that is able to perform consistent stellar PSF photometry across the range of crowding conditions expected in LSST.

The final set of numbers in Table 14, reflecting the analysis of objects classified by ALLFRAME as stars, shows a slight increase in the scatter of photometric measurements. The degradation is likely due to the impact of ALLFRAME detecting fainter, more crowded objects, for which photometry is more difficult. However, the PSF-photometry results are still better than DAOPHOT’s single-image analysis of this field and are essentially equivalent to the sparse-field analysis results presented in Table 8.

14.1.1. Photometry as a Function of Crowding

Given the broad range of stellar densities in these images, we are able to constrain how DAOPHOT’s ability to do PSF photometry degrades as a function of local crowding conditions. To do this we have divided the image up into $200 \times 200$ pixel regions, and select only those objects that ALLFRAME classifies as stars in both runs. We count the total number of such objects in this region, as well as the total number of “bright” objects in this region, where we define “bright” as the brightest 3 magnitudes of objects. We calculate the $\sigma_{\text{mean}}$ from the interquartile range of $\Delta M$ for the bright objects and plot this against the total number of stars in the bin. We normalize this by the area of the box, yielding the local number of stars per pixel, and then multiply by the averaged FWHM of the two images, yielding the approximate number of stars per seeing disk. We fit a line to the relationship of $\Delta M$ versus the number of stars per FWHM$^2$. These results are summarized in Table 15. We show the plots for the $r$-band data in Figure 8. Extrapolation back to an empty field (number of stars = 0) yields numbers that are very close to the SRD requirement on photometric accuracy.

14.2. Photometric Depth

We select stars on an algorithm-by-algorithm basis and find that the peaks of the star count histograms are the same for both DAOPHOT and ALLFRAME, approximately $r = 20.5$, $g = 21.0$, $i = 20.2$ for run 4207. However, ALLFRAME finds approximately 1.5 times the total number of objects in the $g$-band data, 1.3 in the $r$ band, and 1.4 in the $i$ band. This is due to ALLFRAME’s ability to resolve and photometer blended objects.
neighbors that contaminate an object’s sharpness in DAOPHOT, as well as its extra photometric depth. Table 16 characterizes the depth per run and passband. For both algorithms, we list the peak of the histogram (M_{max}), the magnitude bin below which 95% of the stars are contained (M_{95}), and the bin below which 99% of the stars are contained (M_{99}). Using M_{99} as our proxy, ALLFRAME accurately photometers objects nearly 1 mag deeper than in DAOPHOT in the \(g\) band, 0.3 mag in the \(r\) band, and 0.5 mag in the \(i\) band. This is a remarkable improvement considering that we only have two images per passband to work with. The fact that we can combine the constraints from images in different filters into a global analysis allows us to make such improvements in depth.

Figure 9 shows an \(r\) versus \(g - r\) color-magnitude diagram (CMD) of all stars in the SDSS images containing M2. We have not selected against field stars, which contaminate the cluster CMD. For each algorithm, we query for all clustered objects that were classified as stars in both runs and in both passbands to yield the final ensembles of points. ALLFRAME finds 1.7 times the number of stars as DAOPHOT. We plot the averaged magnitudes and colors of the objects, as well as typical error bars on each point in eight magnitude bins.

14.3. Conclusions from Study of M2

The ALLFRAME analysis has shown that it is an encouraging precursor to LSST’s envisioned Deep Detection Pipeline ensemble analysis of imaging data (Roat et al. 2005). We are able to use all images of a given part of the sky to attain extra depth and precision in the measurements of all objects in the field. Potential improvements to this process include regeneration of the PSF during the ensemble analysis, as well as characterization of extended objects.

15. PROCESSING TIME AND SCALABILITY

During processing, we recorded the total elapsed time to run each algorithm on all images. However, during testing we noticed severe degradations in performance during periods of heavy disk access. This is a known problem with the Redundant

![Figure 8: Value of \(\sigma_{\Delta M}\) plotted as a function of local crowding conditions, derived from ALLFRAME analysis of globular cluster M2, for the \(r\)-band data. We divided the image up into multiple regions and for each derived the width of the \(\Delta M\) distribution from the brightest three magnitudes of stars. We normalized the number of all stars in each region by the area of the region and the average FWHM of the two images. The \(x\)-axis reflects the crowding conditions and corresponds to the total number of stars per seeing disk. See the electronic edition of the PASP for a color version of this figure.](image1)

![Figure 9: CMD of M2 reconstructed from DAOPHOT and ALLFRAME analysis. All clustered objects classified by each algorithm as stars in both runs and in both the \(r\) and \(g\) bands were used. We also plot typical error bars in eight magnitude bins. The ALLFRAME CMD contains 70% more points than the DAOPHOT CMD, and reaches approximately 0.3 mag deeper in the \(r\) band. See the electronic edition of the PASP for a color version of this figure.](image2)
Array of Independent Drives (RAID) controller on the host machine and makes the absolute numbers in this section inaccurate. The relative numbers are likely to be less affected.

We do not have information for DOPHOT on run 4207 because the file containing the times for this run was corrupted. We emphasize that the DAOPHOT results are not entirely localizable to the internal algorithms but are also due to inefficiencies in our controlling Perl scripts (§ 5). We fit the trend of processing time with the number of detections and present these results in Table 17. SExtractor is the fastest algorithm, with version 2.3.2 slightly faster than version 2.4.4, primarily due to the overhead in calculating windowed quantities in the latter. There appears to be a minimum threshold of at least 4 s necessary for SExtractor to process an individual stitched image regardless of the number of detections found, due to overhead associated with the reading and writing of data products. DAOPHOT shows a significant trend with number of detections and has the steepest scaling laws. The DOPHOT entry in Table 17 is a bit misleading, as DOPHOT tends to be relatively insensitive to the number of objects ultimately detected in the image. This suggests that much of the processing time is spent on common-mode items such as the PSF generation.

15.1. Additional Testing

In an effort to eliminate the influence of the RAID controller, we also ran time trials on a new computer. We selected four images (two from each run) covering the range of total detections per image found by SExtractor in the r filter. The “stitched” images are approximately 2k × 4k in size. We decided to examine the scaling of resource usage with image size by chopping each image into a 2k × 2k image. We also produce an LSST-sized image by placing a copy of each image next to itself to yield a 4k × 4k image. We store a copy of each image with a variety of bit depths to determine how this might affect SExtractor’s behavior. We store a copy of each image as 16 and 32 bit integers (BITPIX = 16, 32), and as 32 and 64 bit floats (BITPIX = −32, −64). In summary, we have four images with different numbers of objects; we have three copies of each image in different sizes; and we store each of these with four different bit depths. In total, this yields 48 different configurations. Each of these images was SExtracted 50 times in a row to determine the average elapsed time per image, averaging over any extraneous system load. SExtractor was run while there were no other tasks queued on the machine for the duration of each run. We monitored the memory usage of each process as a function of time by scanning the file/proc/PID/status every 0.5 s. We extract the values VmSize and VmRSS. VmSize is the total amount of memory required by this program, and VmRSS is the “resident set size” (the amount actually in memory at a given moment). We extracted the total processing time by using the executable /usr/bin/time and summing the user CPU and system CPU times—each process had 98% or greater of the CPU. Table 18 lists the results of these trials.

We first examine the profiling as a function of image bit depth. The maximum memory used by SExtractor is not a function of image bit depth for a given-sized image. This suggests that SExtractor translates an image into a “native” bit depth before processing. The total processing times for BITPIX of 16,
32, and −32 are very similar; the BITPIX = 64 images take on average 10% longer to process, suggesting significant overhead in translating from 64 bit images. We restrict our analysis henceforth to 32 bit float images.

We next look at the memory consumed as a function of time for a given run. Since we only sample the memory usage in 0.5 s intervals, this will be somewhat poorly determined for the short analyses. We choose to make representative plots using the last image in Table 18. Figure 10 shows the average memory usage as a function of time for the three image sizes. Note that the total processing time shown here can be up to 0.5 s smaller than the values listed in Table 18 due to our coarse sampling.

It is interesting to note the memory consumption profiles generally differ due to the different processing times, but the maximum memory used does not scale directly with the image size or the total number of objects. The memory requirements grow only marginally more expensive, suggesting that SExtractor undertakes an effective degree of intelligent memory management. For example, the 4k × 4k image consumes less than twice as much memory as the 2k × 4k image.

We next examine the total processing time as a function of the number of objects in the image. These data are plotted in Figure 11. We plot the data from the 2k × 2k images as circles, 2k × 4k as squares, and 4k × 4k as triangles. A linear regression yields the relationship \( y = 0.5468x + 0.0007 \). Comparing this to the entries in Table 17 is instructive. The zero-point processing time of 0.5 s is much shorter than previous results of ~1 s, almost certainly due to the aforementioned RAID issues impeding disk I/O. The slope is similar: every ~1300 objects being measured adds an additional second of processing time. We regard these tests on this machine to yield the most reliable timing results.

15.2. Processing Time Conclusions

SExtractor version 2.3.2 was the fastest of these algorithms. However, with slightly longer processing time we gain a considerable amount of accuracy in the position and shapes of detected objects by using the “windowed” parameters from SExtractor 2.4.4.

Disk access is a fundamental issue that can significantly impede image processing tasks.

The timing tests in § 15.1 produce the most reliable absolute numbers. If we assume that the LSST focal plane is populated with 4k × 4k devices, than we expect that a single detector may be photometered in \((0.5 \text{ s})(2.8 \text{ GHz}) = 1.4 \text{ GHz s}\), with an additional overhead of 1.4 GHz s for every 1300 objects in the image. We have not tested how these numbers scale with processor speed.

16. SUMMARY OF RESULTS

16.1. Star-Galaxy Separation

Each package undertakes some measure of object classification. In all cases, the benchmark profile is the PSF. DAOPHOT and DOPHOT compare each object to the PSF profile. SExtractor compares the width of each object with the input PSF FWHM. In comparison, Photo compares the flux measured using the PSF to the flux from galaxy model fits.

Both DOPHOT and SExtractor fared poorly compared to DAOPHOT and Photo (Tables 2 and 3). However, SExtractor has the option to use neural-network filters to enhance its performance. DAOPHOT does a good job at object classification.
but does not explicitly compute object moments. Objects for which DAOPHOT and Photo disagree tend to be drawn from the stellar locus (Fig. 4).

Photo is the most advanced package in this task, with SExtractor having the most potential for improvement through add-on software such as EyE.

16.2. Photometry

Both DAOPHOT and Photo are able to satisfy LSST’s science requirements on photometric accuracy (0.005 mag unless precluded by photon statistics) for aperture measurements only. This is realized in the \(g\), \(r\), and \(i\)-band data sets. PSF photometry is unable to reach this accuracy and consistently falls short by a factor of \(\sim 2–3\). DAOPHOT provides marginally better results than Photo in both aperture and PSF photometry in our normal analysis. DOPHOT consistently underperforms in both aperture and PSF photometry. SExtractor provides adequate aperture photometry but does not yet have the capability to easily build and use a PSF model. These results are summarized in Table 4 (for Photo-selected stars) and Table 8 (for algorithm-selected stars).

The additional scatter in the PSF magnitudes can be traced back to inadequate aperture corrections to the PSF flux. We highlight that the determination of this quantity, as well as its spatial variation across an image, is a crucial issue in LSST algorithm development.

From our analysis of globular cluster M2, we find that DAOPHOT is able to provide PSF magnitudes in a crowded field with an accuracy similar to a sparse-field analysis. A stacked analysis of the data using ALLFRAME yields an improvement of approximately 25% (Table 14) in photometric accuracy, and a passband-dependent increase in photometric depth (Table 16). We find a marginal degradation in photometric accuracy with local crowding conditions (Table 15). ALLFRAME is able to maintain 2% accuracy in \(r\)-band PSF photometry in crowding of up to 0.12 stars per PSF FWHM (\(\sim 880\) stars arcmin\(^{-1}\) in 0.7” seeing).

16.3. Shape Measurements

SExtractor and Photo are the only packages that provide reliable estimates of object shapes, using second moment analysis. Photo is also the only package that also fits galaxy models (exponential, de Vaucouleurs) to each object. SExtractor version 2.3.2 uses isophotal second moments, which degrade rapidly as a function of magnitude compared to Photo’s adaptive second moments (e.g., left panel of Fig. 6). These measurements should not be used to measure the shapes of stars. SExtractor versions 2.4.4 and greater use “windowed” second moments that yield ellipticities comparable to Photo’s (e.g., right panel of Fig. 6). Photo and SExtractor 2.4.4’s stellar ellipticity measurements are extremely consistent, their differences having an rms of 0.001–0.004 (Table 9). This is more than a factor of 10 smaller than LSST’s science requirement that the median of the distribution be no larger than 0.04, indicating that the algorithmic contribution to the stellar ellipticity distribution should be negligible.

16.4. Centroiding

By comparing the calculated \(x\), \(y\) centroids of objects to Photo’s centroids, we find very strong systematic trends in isophotal centroiding accuracy as a function of magnitude for SExtractor version 2.3.2 (top panel of Fig. 7; Table 11). The windowed centroids in SExtractor version 2.4.4 and greater remedy this systematic (bottom panel of Fig. 7). The centroiding rms at the bright end (compared to Photo) for most algorithms is 1/100 the PSF FWHM. An algorithm-to-algorithm comparison yields a typical centroiding rms of better than 1/200 the FWHM, with Photo the clear outlier due to its absolute astrometry corrections (Tables 12).

The LSST relative astrometry requirement of 0.005 is not likely to be violated in software. The absolute astrometry requirements of 0.01 may require corrections similar to Photo’s.

16.5. Summary

The one area where current algorithms do not clearly exceed the constraints set out in LSST’s SRD is in photometric accuracy. Photo and DAOPHOT are able to deliver the requisite quality, but only in aperture photometry, and then just at the threshold of acceptability. Advances in PSF modeling and in wide-field aperture corrections and sky subtraction are likely needed to ensure that the software can deliver on the promise of LSST.

To summarize Photo’s advantages: its aperture photometry meets the LSST science requirements; its PSF photometry is as good as DAOPHOT; it is reliably able to discriminate stars from galaxies; it is the only algorithm that does galaxy model fitting; the five-band simultaneous photometry is very similar to the envisioned LSST Deep Detection analysis; and its star-galaxy deblender is robust under a variety of conditions. The disadvantages of Photo are that it is not very flexible with respect to the format of input data, only operating on SDSS images; the code as designed is not very portable; the deblender is not designed for crowded fields.

To summarize DAOPHOT’s advantages: its PSF photometry is the best among the algorithms considered here; star-galaxy separation is surprisingly robust; it provides the best solution for point-source photometry in crowded fields; ALLFRAME is also a useful Deep Detection precursor algorithm. Its disadvantages are that it is relatively slow and it does no galaxy characterization.

To summarize DOPHOT’s advantages: it is easily pipelined and will take almost any input data. Its disadvantages are that its PSF does not vary spatially and that it returns the poorest results with respect to both photometry and astrometry (excluding SExtractor isophotal centroids).
Finally, to summarize SExtractor’s advantages: it is very fast and the code is very portable; its aperture photometry returns acceptable results; its windowed shapes are as good as Photo’s adaptive shapes; the windowed centroids are as good as PSF centroids; the deblending model is very extensible; and the inclusion of neural networking for object classification is novel and potentially very powerful. Its disadvantages are that there is no easily accessible PSF modeling, and the isophotal shape and positional measurements may be significantly biased at faint magnitudes.

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