Large Synoptic Survey Telescope
Data Management Applications Design

Mario Jurić*, R.H. Lupton, T. Axelrod, J.F. Bosch, P.A. Price,
G.P. Dubois-Felsmann, Ž. Ivezić, A.C. Becker, J. Becla,
A.J. Connolly, J. Kantor, K-T Lim, D. Shaw,
for the LSST Data Management

Tuesday 21st June, 2016, 12:54hrs

*Please direct comments to <mjuric@lsst.org>.

Abstract

The LSST Science Requirements Document (the LSST SRD) specifies a set of data product guidelines, designed to support science goals envisioned to be enabled by the LSST observing program. Following these guidlines, the details of these data products have been described in the LSST Data Products Definition Document (DPDD), and captured in a formal flow-down from the SRD via the LSST System Requirements (LSR), Observatory System Specifications (OSS), to the Data Management System Requirements (DMSR). The LSST Data Management subsystem's responsibilities include the design, implementation, deployment and execution of software pipelines necessary to generate these data products. This document, in conjunction with the UML Use Case model (LDM-134), describes the design of the scientific aspects of those pipelines.

Contents

1 Preface

The purpose of this document is to describe the design of pipelines belonging to the Applications Layer of the Large Synoptic Survey Telescope (LSST) Data Management system. These include most of the core astronomical data processing software that LSST employs.

The intended audience of this document are LSST software architects and developers. It presents the baseline architecture and algorithmic selections for core DM pipelines. The document assumes the reader/developer has the required knowledge of astronomical image processing algorithms and solid understanding of the state of the art of the field, understanding of the LSST Project goals and concepts, and has read the LSST Science Requirements (SRD) as well as the LSST Data Products Definition Document (DPDD).

This document should be read in conjunction with the LSST DM Applications Use Case Model (LDM-134). They are intended to be complementary, with the Use Case model capturing the detailed (inter)connections between individual pipeline components, and this document capturing the overall goals, pipeline architecture, and algorithmic choices.

Though under strict change control[1], this is a ***living document***. Firstly, as a consequence of the "rolling wave" LSST software development model, the designs presented in this document will be refined and made more detailed as particular pipeline functionality is about to be implemented. Secondly, the LSST will undergo a period of construction and commissioning lasting no less than seven years, followed by a decade of survey operations. To ensure their continued scientific adequacy, the overall designs and plans for LSST data processing pipelines will be periodically reviewed and updated.

[1] LSST Docushare handle for this document is `LDM-151`.

2 Introduction

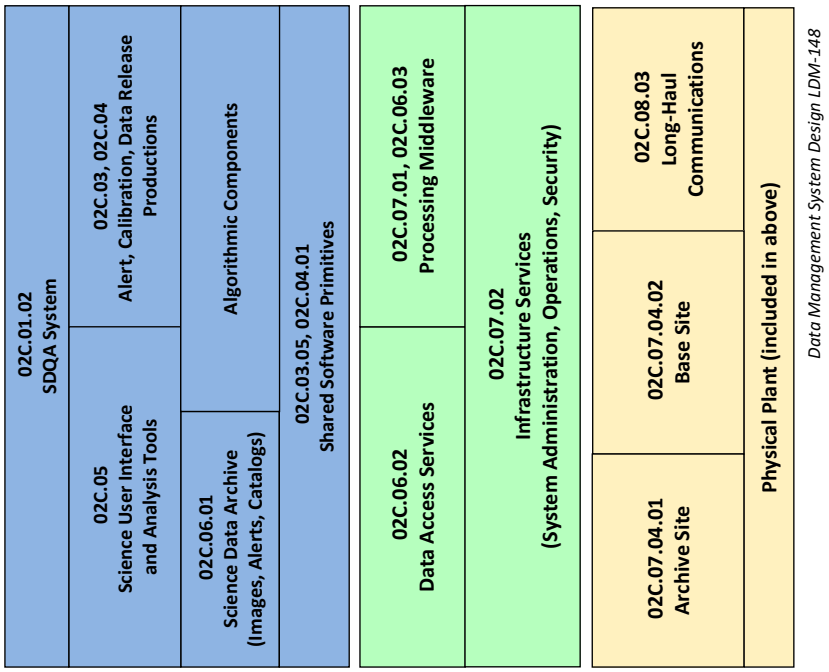
2.1 LSST Data Management System

To carry out this mission the Data Management System (DMS) performs the following major functions:

- Processes the incoming stream of images generated by the camera system during observing to produce transient alerts and to archive the raw images.
- Roughly once per year, creates and archives a Data Release ("DR"), which is a static self-consistent collection of data products generated from all survey data taken from the date of survey initiation to the cutoff date for the Data Release. The data products (described in detail in the DPDD), include measurements of the properties (shapes, positions, fluxes, motions, etc.) of all detected objects, including those below the single visit sensitivity limit, astrometric and photometric calibration of the full survey object catalog, and limited classification of objects based on both their static properties and time-dependent behavior. Deep coadded images of the full survey area are produced as well.
- Periodically creates new calibration data products, such as bias frames and flat fields, that will be used by the other processing functions, as necessary to enable the creation of the data products above.
- Makes all LSST data available through interfaces that utilize, to the maximum possible extent, community-based standards such as those being developed by the Virtual Observatory ("VO"), and facilitates user data analysis and the production of user-defined data products at Data Access Centers ("DAC") and at external sites.

The overall architecture of the DMS is discussed in more detail in the Data Management System Design (DMSD) document. The overall architecture of the DMS is shown in Figure 1.

This document discusses the role of the Applications layer in the first three functions listed above (the functions involving *science pipelines*). The fourth is discussed separately in the SUI Conceptual Design Document (SUID).



Application Layer (LDM-151)

- Scientific Layer
- Pipelines constructed from reusable Algorithmic Components
- Data Products represented by Shared Software Primitives
- Object-oriented, python, C++ Custom Software

Middleware Layer (LDM-152)

- Portability to clusters, grid, other
- Provide standard services so applications behave consistently (e.g. provenance)
- Preserve performance (<1% overhead)
- Custom Software on top of Open Source, Off-the-shelf Software

Infrastructure Layer (LDM-129)

- Distributed Platform
- Different sites specialized for real-time alerting vs peta-scale data access
- Off-the-shelf, Commercial Hardware & Software, Custom Integration

Figure 1: Architecture of the Data Management System

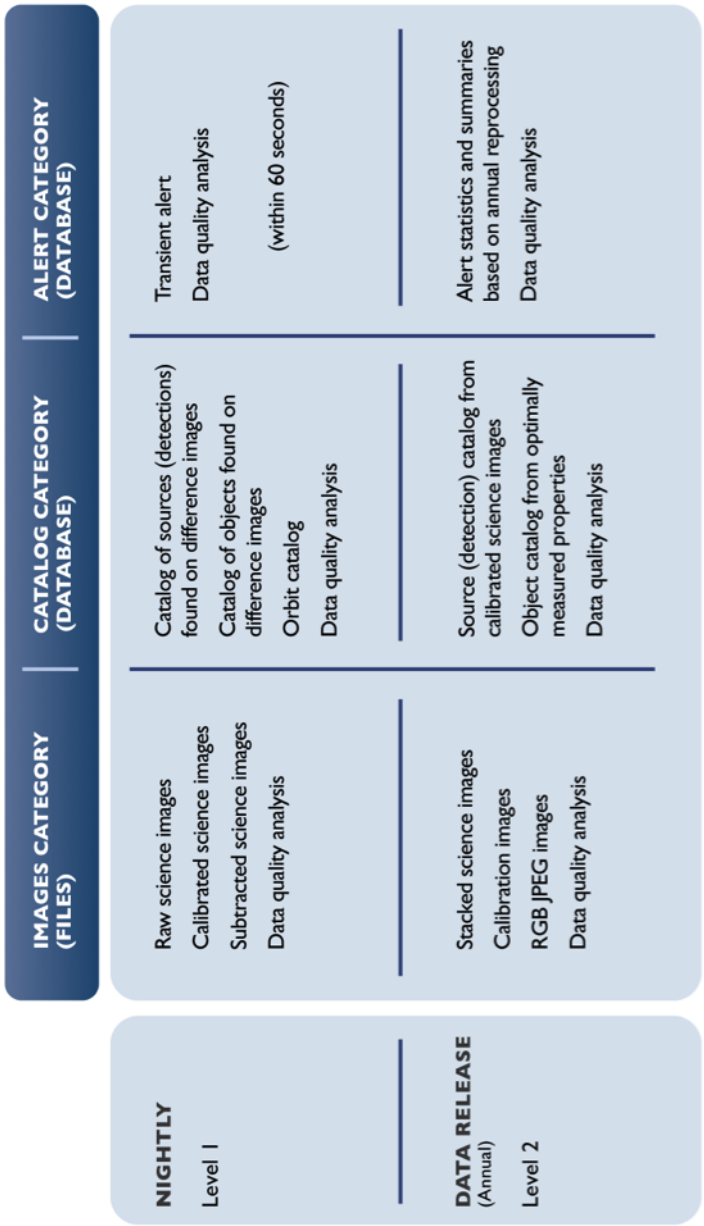


Figure 2: Organization of LSST Data Products

2.2 Data Products

The LSST data products are organized into three groups, based on their intended use and/or origin. The full description is provided in the Data Products Definition Document (DPDD); we summarize the key properties here to provide the necessary context for the discussion to follow.

- **Level 1** products are intended to support timely detection and follow-up of time-domain events (variable and transient sources). They are generated by near-real-time processing the stream of data from the camera system during normal observing. Level 1 products are therefore continuously generated and / or updated every observing night. This process is of necessity highly automated, and must proceed with absolutely minimal human interaction. In addition to science data products, a number of related Level 1 "SDQA"[2] data products are generated to assess quality and to provide feedback to the Observatory Control System (OCS).

- **Level 2** products are generated as part of a Data Release, generally performed yearly, with an additional data release for the first 6 months of survey data. Level 2 includes data products for which extensive computation is required, often because they combine information from many exposures. Although the steps that generate Level 2 products will be automated, significant human interaction may be required at key points to ensure the quality of the data.

- **Level 3** products are generated on any computing resources anywhere and then stored in an LSST Data Access Center. Often, but not necessarily, they will be generated by users of LSST using LSST software and/or hardware. LSST DM is required to facilitate the creation of Level 3 data products by providing suitable APIs, software components, and computing infrastructure, but will not by itself create any Level 3 data products. Once created, Level 3 data products may be associated with Level 1 and Level 2 data products through database federation. Where appropriate, the LSST Project, with the agreement of the Level 3 creators, may incorporate user-contributed Level 3 data product pipelines into the DMS production flow, thereby promoting them to Level 1 or 2.

[2]Science Data Quality Analysis

The organization of LSST Data Products is shown in Figure 2.

Level 1 and Level 2 data products that have passed quality control tests will be accessible to the public without restriction. Additionally, the source code used to generate them will be made available, and LSST will provide support for builds on selected platforms.

The pipelines used to produce these public data products will also produce many intermediate data products that may not be made publically available (generally because they are fully superseded in quality by a public data product). Intermediate products may be important for QA, however, and their specification is an important part of describing the pipelines themselves.

2.3 Data Units

In order to describe the components of our processing pipelines, we first need standard nomenclature for the units of data the pipeline will process.

The smallest data units are those corresponding to individual astrophysical entities. In keeping with LSST conventions, we use "object" to refer to the astrophysical entity itself (which typically implies aggregation of some sort over all exposures), and "source" to refer to the realization of an object on a particular exposure. In the case of blending, of course, these are just our best attempts to define distinct astrophysical objects, and hence it is also useful to define terms that represent this process. We use "family" to refer to group of blended objects (or, more rarely, sources), and "child" to refer to a particular deblended object within a family. A "parent" is also created for each family, representing the alternate hypothesis that the blend is actually a single object. Blends may be hierarchical; a child at one level may be a parent at the level below.

LSST observations are taken as a pair of 15-second "snaps"; together these constitute a "visit". Because snaps are typically combined early in the processing (and some special programs and survey modes may take only a single snap), visit is much more frequently used as a unit for processing and data products. The image data for to a visit is a set of 189 "CCD" or "sensor" images. CCD-level data from the camera is further data divided across the 16 amplifiers within a CCD, but these are also combined at an early stage, and the 3×3 CCD "rafts" that play an important role in the hardware design are relativley unimportant for the pipeline. This leaves visit and CCD the main identifiers of most exposure-level data products and pipelines.

Our convention for defining regions on the sky is deliberately vague; we

hope to build a codebase capable of working with virtually any pixelization or projection scheme (though different schemes may have different performance or storage implications). Our approach involves two region concepts: "tracts" and "patches". A tract is a large region with a single Cartesian coordinate system; we assume it is larger than the LSST field of view, but its maximum size is essentially set by the point at which distortion in the projection becomes significant enough to affect the processing (by e.g. breaking the assumption that the PSF is well-sampled on the pixel grid). Tracts are divided into patches, all of which share the tract coordinate system. Most image processing is perfomed at the patch level, and hence patch sizes are chosen largely to ensure that patch-level data products and processing fit in memory. Both tracts and patches are defined such that each region overlaps with its neighbors, and these overlap regions must be large enough that any individual astronomical object is wholly contained in at least one tract and patch. In a patch overlap region, we expect pixel values to be numerically equivalent (i.e. equal up to floating point round-off errors) on both sides; in tract overlaps, this is impossible, but we expect the results to be scientifically consistent. Selecting larger tracts and patches thus reduces the overall fraction of the area that falls in overlap regions and must be processed multiple times, while increasing the computational load for processing individual tracts and patches.

2.4 Science Pipelines Organization

As shown in Figure 1, the Applications Layer is itself split into three levels. In sections 3, 4, and 5, we describe the Alert Production, Calibration Products Production, and Da ta Release Production (respectively), breaking them down into *pipelines*. In this document, a pipeline is a high-level combination of algorithms that is intrinsically tied to its role in the production in which it is run. For instance, while both Alert Production and Data Release Production will include a pipeline for single-visit processing, these two pipelines are *distinct*, because the details of their design depend very much on the context in which they are run. Section 6 describes the Science Data Quality Analysis System, a collection of pipelines and mini-productions designed to assess and continuously validate the quality of both the data and the processing system. The SDQA System is not a single production; its components are either directly integrated into other productions or part of a set of multiple mini-productions run on different cadences.

Pipelines are largely composed of Algorithmic Components: mid-level algorithmic code that we expect to reuse (possibly with different configuration) across different productions. These components constitute the bulk of the new code and algorithms to be developed for Alert Production and Data Release Production, and are discussed in section 8. Most algorithmic components are applicable to any sort of astronomical imaging data, but some will be customized for LSST.

The lowest level in the Applications Layer is made up of our shared software primitives: libraries that provide important data structures and low-level algorithms, such as images, tables, coordinate transformations, and nonlinear optimizers. Much (but not all) of this content is astronomy-related, but essentially none of it is specific to LSST, and hence we can and will make use of third-party libraries whenever possible. These primitives also play an important role in connecting the Science User Interface Toolkit and Level 3 processing environment with Level 1 and Level 2 data products, as they constitute the programmatic representation of those data products. Shared software primitives are discussed in section 9.

3 Level 1 Pipelines

3.1 Single Frame Processing Pipeline (WBS 02C.03.01)

Single Frame Processing (SFM) Pipeline is responsible for reducing raw or camera corrected image data to *calibrated exposures*, and the detection and measurement of `Sources` (using the components functionally a part of the Object Characterization Pipeline).

3.1.1 Key Requirements

SFM pipeline functions include:

- Assembly of per-amplifier images to an image of the entire CCD;
- Instrumental Signature Removal;
- Cosmic ray rejection and snap combining;
- Per-CCD determination of zeropoint and aperture corrections;
- Per-CCD PSF determination;
- Per-CCD WCS determination and astrometric registration of images;
- Per-CCD sky background determination;
- Source detection and measurement on single frame images
- Generation of metadata required by the OCS

Calibrated exposure produced by the SFM pipeline must possess all information necessary for measurement of source properties by single-epoch Object Characterization algorithms.

It shall be possible to run this pipeline in two modes: a "fast" mode needed in nightly operations for Level 1 data reductions where no source characterization is done beyond what's required for zero-point, PSF, sky, and WCS determination (image reduction); and a "full" mode that will be run for Level 2 data reductions. It should be possible for this pipeline or a subset of this pipeline to be run at the telescope facility during commissioning and operations. *AJC: is the level 2 a requirement*

3.1.2 Baseline Design

Single Frame Processing pipeline will be implemented as a flexible framework where different data can be easily treated differently, and new processing steps can be added without modifying the stack code.

It will consist of three primary components:

- A library of useful methods that wrap a small number of atomic operations (e.g., `interpolateFromMask`, `overscanCorrection`, `biasCorrection`, etc.)
- A set of classes (`Task`s) that perform higher level jobs (e.g., `AssembleCcdTask`, or `FringeTask`), and a top level class to apply corrections to the input data in the proper order. This top level class can be overridden in the instrument specific `obs_*` packages, making the core SFM pipeline camera agnostic.
- A top-level Task to run the SFM pipeline.

In the paragraphs to follow, we describe the adopted baseline for key SFM algorithms. If not discussed explicitly, the algorithmic baseline for all other functionallity is assumed to be the same as that used by SDSS *Photo* pipeline [18].

3.1.2.1 Instrumental Signature Removal:

Input Data:

- Camera corrected images (crosstalk, overscan, linearity)
- Sensor defect lists
- Metadata including electronic parameters (saturation limits, readnoise, electronic footprint)

Output Data:

- Calexp images

Actions in case of failure:

In the case camera data are not available due to a network outage that is longer than the data buffer at the summit the ISR processing will work on raw images (i.e. without the camera corrections) and be run in a batch mode.

Alternative procedures:

Subtasks:

- Mask defects and saturation
- Assembly
- Full frame corrections: Dark, Flats (includes fringing)
- Pixel level corrections: Brighter fatter, static pixel size effects
- **QUESTION is this run prior to pixel level corrections** Interpolation of defects and saturation
- CR rejection
- Generate snap difference
- Snap combination

3.1.2.2 PSF determination and background determination:

Iterative procedure to fit and remove background, identify sources to 5σ, select bright sources (50σ), and fit a PSF model. Convergence criteria for the procedure is not defined but the default procedure assumes three iterations.
Input Data:

- Access to ICexp images from ISR

Output Data

- IC images
- IC source catalog

Actions in case of failure
Alternative procedures

Subtasks:

- Background estimation
- Source detection

- Selection of PSF candidate stars based on signal-to-noise (default 50 σ) and isolate sources
- Single CCD PSF determination

3.1.2.3 Source measurement: Input Data:

- Access to background subtracted ICexp images
- Access to sources detected from ICexp images

Output Data:

- IC source catalog with measurements

Actions in case of failure
Alternative procedures

Subtasks:
Measurement on sources detected for the PSF estimation using a subset of parameters as required by the Alert Detection. Measurements are for all sources not just bright subset.

- Source measurement - Single visit measurement for detected sources
- Aperture correction for detected sources

3.1.2.4 Photometric and Astrometric calibration:
Input Data:

- Access to background subtracted ICexp images
- Access to sources detected from ICexp images
- Butler access to DRP's internal reference catalog
- Calexp images (persisted)
- Calibrated source catalog

- OCS PSF, WCS, metadata (TBD)

Actions in case of failure

Subtasks:

Photometric and astrometric calibration performed at the scale of a single sensor (extended to the scale of a visit depending on required fidelity)

- Sensor level source association between the DRP reference catalog and sources detected during PSF characterization
- CCD level photometric solution
- Remove known astrometric distortions
- CCD level composed astrometric solution to residuals
- Output information for OCS telemetry: WCS ACTION clarify OCS interactions

Alternative procedures

Dependent on accuracy of single sensor photometric and astrometric calibrations

- Visit level photometric solution
- Visit level composed astrometric solution to residuals if required

3.1.3 Prototype Implementation

The prototype codes are available in the following repositories: `https://github.com/lsst/ip_isr`, `https://github.com/lsst/meas_algorithms`, `https://github.com/lsst/meas_astrom`, `https://github.com/lsst-dm/legacy-meas_mosaic`, `https://github.com/lsst/pipe_tasks`.

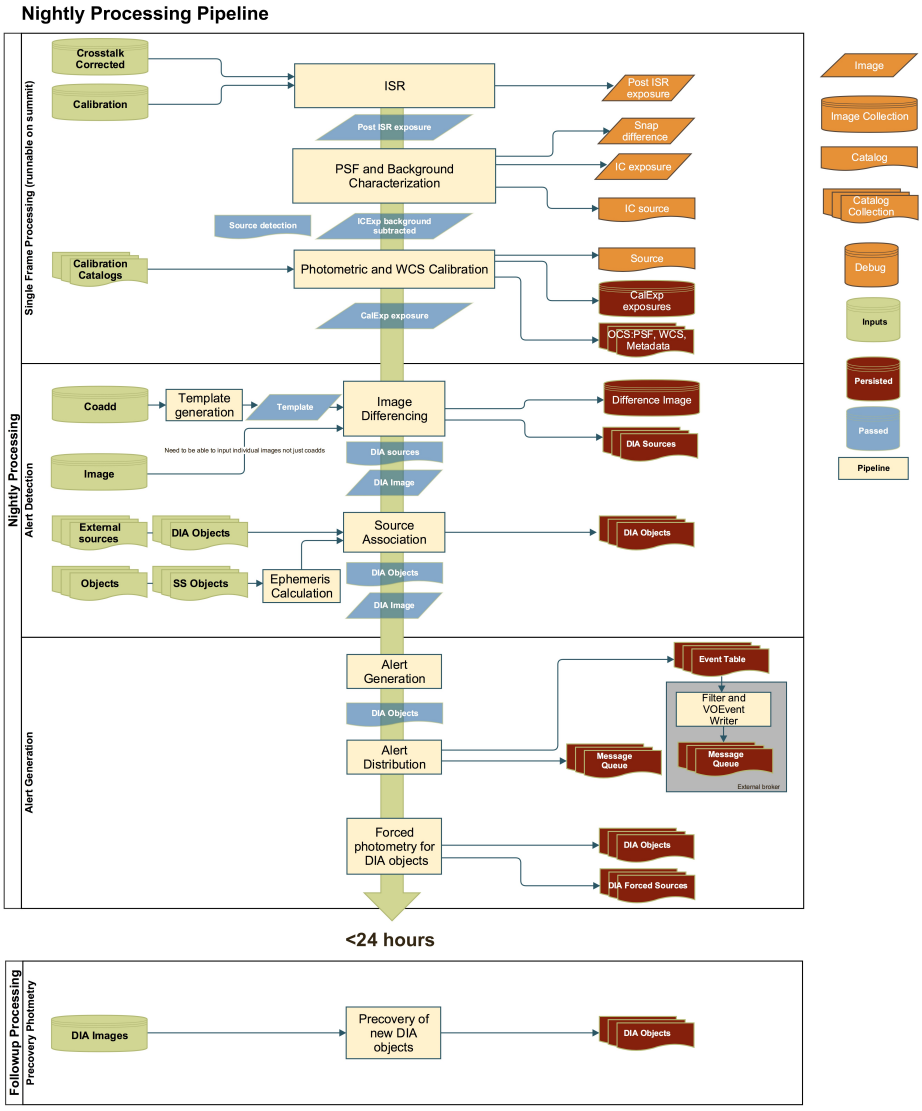


Figure 3: The nightly processing flowchart describing the flow of images and data through single frame processing, image differencing, alert generation and production

3.2 Alert Detection (WBS 02C.03.04)

Input Data:

- Butler access to Coadd images from DRP that overlap spatially with CalExp images
- Access to DIAObjects that overlap spatially with CalExp images
- Access to Objects that overlap spatially with CalExp images
- Access to SSObjects whose ephemerides overlap spatially with CalExp images
- Internal reference catalog for CalExp from DRP
- PSF measured from the science image.
- Data structures for the real-bogus classifier

Output Data

- DIAimage persisted
- DIASources persisted
- DIAObjects persisted
- DIA forced photometry persisted

Actions in case of failure:
Alternative procedures:

- Butler access to CalExp images from DRP that overlap spatially with current CalExp image for template generation

3.2.1 Key Requirements

The alert detection pipeline shall difference a visit image against a deeper template, and detect and characterize sources in the difference image in the time required to achieve the 60 second design goal for Level 1 alert processing (current timing allocation: 24 seconds). The algorithms employed by the pipeline shall result in purity and completeness of the sample as required by the DMSR . Image differencing shall perform as well in crowded as in uncrowded fields.

3.2.2 Baseline Design

3.2.2.1 Template Generation

By either querying for Coadd Images that spatially overlap with a given CalExp or for a DCR differential chromatic refraction corrected template (see Retrieve Diffim Template) template image.
Subtasks:

- Query for Coadd images that are within a given time interval (default 2 years) of the current sensor image, and are within allowable airmass limits (default XXX). seexs template retrieval
- An alternate approach will be to return an interpolated, DCR-corrected template based on a model of the effect of DCR (see DCR template generation). The direction of the DCR correction will be aligned with the "parallactic angle".

3.2.2.2 Image differencing

Model the matching kernel and its spatial variation using a regression approach and a set of basis functions
Subtasks:

- Match DRP sources and sources from SFP
- Determine a relative astrometric solution
- Warp the template and measurements to the science image frame
- Determine the appropriate PSF matching sources

- Decorrelate the science image with an estimate of the science PSF (pre-convolution)
- Compute the PSF matching kernel and spatial model using ZOGY approach
- Difference the science and template images
- Apply a correction for correlated noise
- Difference image source detection to generate DIASources
- Difference image source measurement: dipole fit, trailed source measurement
- Measure flux on snap difference for all DIASources

3.2.2.3 Real-Bogus classification

Initial classification step to identify false positives in the image difference sources. Training of the classifier will be undertaken outside of the nightly processing and will utilize a training sample of real variable sources and artifacts based on labelled data. Labels will be derived from simulated data and visually classified sources.

Subtasks:

- The data structures for the real-bogus machine learning algorithm(s) will be loaded
- A random forest or other probabilistic classification algorithm will be applied to the DIASources
- Update the DIASources with the probabilistic classification
- Prune the DIASource list based on classifier results

3.2.2.4 Ephemeris Calculation

Input Data:
Output Data:
Actions in case of failure:
Alternative procedures:

Subtasks:

- Calculate positions for all solar system objects that may overlap the current exposure.

3.2.2.5 Source Association

Input Data:

- Access to DIAObjects and that overlap spatially with CalExp images
- Access to Objects that overlap spatially with CalExp images
- Access to SSObjects whose ephemerides overlap spatially with CalExp images
- Internal reference catalog for CalExp from DRP
- PSF measured from the science image.
- Data structures for the real-bogus classifier

Output Data

- DIAimage persisted
- DIASources persisted
- DIAObjects persisted
- DIA forced photometry persisted

Subtasks:

- Given the time of an observation and the motion of the sources, propagate positions of all sources (SSObjects and DIASources).
- Using the WCS determine the sensor coordinates for all DIAObjects in the catalog
- Match all DIASources to all DIAObject catalog positions using a probabilistic matching algorithm

- Update associated DIAObjects with aggregate quantities e.g. position and flux (in a 30 day rolling wind)
- Perform forced photometry of all DIAObjects that intersect with the frame.

3.2.3 Prototype Implementation

The prototype code is available at `https://github.com/lsst/ip_diffim`. The current prototype, while functional, will require a partial redesign to be transfered to construction to address performance and extensibility concerns.

3.3 Alert Generation Pipeline (WBS 02C.03.03)

3.3.1 Key Requirements

Alert Generation Pipeline shall take the newly discovered `DIASources` and all associated metadata as described in the DPDD, and generate alert packets in `VOEvent` format. It will transmit these packets to VO Event Brokers, using standard IVOA protocols (eg., VOEvent Transport Protocol; VTP). End-users will primarily use these brokers to classify and filter events for subsets fitting their science goals.

To directly serve the end-users, the Alert Generation Pipeline shall provide a basic, limited capacity, alert filtering service. This service will run at the LSST U.S. Archive Center (at NCSA). It will let astronomers create simple filters that limit what alerts are ultimately forwarded to them. These *user defined filters* will be possible to specify using an SQL-like declarative language, or short snippets of (likely Python) code.

3.3.2 Baseline Design

Input Data:

- Access to DIAObjects that overlap spatially with CalExp images
- Access to Template image that overlap spatially with CalExp images

Output Data

- DIA event table persisted
- VOEvents

3.3.2.1 Alert generation

Subtasks:

- Generate postage stamps for all DIASources: direct image and difference image
- Push alert records to alert database

3.3.2.2 Alert Distribution

Subtasks:

- Persist events within an event table (details TBD)
- Filter event records (for content as well as for events) to generate VOEvents
- Push VOEvents to a messaging queue that persists for a finite period (default length 30 days)

3.3.2.3 Forced Photometry on all DIAObjects

Subtasks:

- Compute forced photometry on all DIAObjects in the field. This does not end up in the alerts.
- Update the DIA Object forced photometry tables

3.3.3 Prototype Implementation

3.4 Precovery Photometry Pipeline

Input Data:

- Butler access to DIA images within finite time interval (default 30 days)
- Butler access to DIAobjects detected from the previous night with no associations

Output Data

- Updated and persisted forced photometry tables for all newly detected DIAobjects

3.4.1 Key Requirements

Within 24 hrs.

3.4.1.1 Precovery of new DIAObjects

Subtasks:

- Force photometer in difference images for all new DIAObjects for the past 30 days.

3.5 Moving Object Pipeline (WBS 02C.03.06)

3.5.1 Key Requirements

The Moving Object Pipeline System (MOPS) has two responsibilities within LSST Data Management:

- First, it is responsible for generating and managing the Solar System[3] data products. These are Solar System objects with associated Keplerian orbits, errors, and detected `DIASources`. Quantitatively, it shall be capable of detecting 95% of all Solar System objects that meet the findability criteria as defined in the OSS . The software components implementing this function are known as ***DayMOPS***.
- The second responsibility of the MOPS is to predict future locations of moving objects in incoming images so that their sources may be associated with known objects; this will reduce the number of spurious transient detections and appropriately flag alerts to detections of known Solar System objects. The software components implementing this function are known as ***NightMOPS***.

3.5.2 Baseline Design

3.5.2.1 Generate Tracklets

Output Data?
Anscillary Products?
Actions in case of failure?
Alternative procedures?

Subtasks:

- Make all tracklet pairs
- Merge multiple chained observation into single longer tracklets
- Purge any tracklets inconsistent with the merged tracklets

[3] Also sometimes referred to as 'Moving Object'

3.5.2.2 Attribution and precovery

Output Data?
Anscillary Products?
Actions in case of failure?
Alternative procedures?

Subtasks:

- Predict locations of known Solar System objects
- Match tracklet observation to predicted ephimerides taking into account velocity
- Update SSObjects
- Possibly iterate

3.5.2.3 Fit Orbits

Output Data?
Anscillary Products?
Actions in case of failure?
Alternative procedures?

Subtasks:

- Merge unassociated tracklets into tracks.
- Fit orbits to all tracks.
- Purge unphysical tracks.
- Update SSObjects
- Possibly iterate

3.5.2.4 Association and Precovery: New SSObjects

Output Data?
Anscillary Products?
Actions in case of failure?
Alternative procedures?

Subtasks:

- Do association and precovery just for SSObjects just found
- Update SSObjects

3.5.2.5 Merge Orbits

Output Data?
Anscillary Products?
Actions in case of failure?
Alternative procedures?

Subtasks:

- Merge orbits with high probability of being the same orbit into a single SSObject

3.5.3 Prototype Implementation

Prototype MOPS codes are available at `https://github.com/lsst/mops_daymops` and `https://github.com/lsst/mops_nightmops`. We expect it will be possible to transfer a significant fraction of the existing code into Construction. Current DayMOPS prototype already performs within the computational envelope envisioned for LSST Operations, though it does not yet reach the required completeness requirement.

4 Calibration Products Production

4.1 Calibration Products Pipeline (WBS 02C.04.02)

4.1.1 Key Requirements

The work performed in this WBS serves two complementary roles:

- It will enable the production of calibration data products as required by the Level 2 Photometric Calibration Plan (LSE-180) and other planning documents [20][4]. This includes both characterization of the sensitivity of the LSST system (optics, filters and detector) and the transmissivity of the atmosphere.
- It will characterize of detector anomalies in such a way that they can be corrected either by the instrument signature removal routines in the Single Frame Processing Pipeline (WBS 02C.03.01) or, if appropriate, elsewhere in the system;
- It will manage and provide a catalog of optical ghosts and glints to other parts of the system upon demand.

4.1.2 Baseline Design

4.1.2.1 Instrumental sensitivity We expect laboratory measurements of the filter profiles. We further baseline the development of a procedure for measuring the filter response at 1 nm resolution using the approach described in [20].

We baseline the following procedure for creating flat fields:

1. Record bias/dark frames;
2. Use "monochromatic" (1 nm) flat field screen flats with no filter in the beam to measure the per-pixel sensitivity;
3. Use a collimated beam projector (CBP) to measure the quantum efficiency (QE) at a set of points in the focal plane, dithering those points to tie them together;

[4] Resolving contradictions between these documents is out of scope here.

4. Combine the screen and CBP data to determine the broad band (10–100 nm) QE of all pixels;

5. Fold in the filter response to determine the 1 nm resolution effective QE of all pixels.

This WBS is responsible for the development of the data analysis algorithms and software required and the ultimate delivery of the flat fields. Development and commissioning of the CBP itself, together with any other infrastructure required to perform the above procedure, lies outwith Data Management (see 04C.08 *Calibration System*).

4.1.2.2 Atmospheric transmissivity Measurements from the auxiliary instrumentation—to include the 1.2 m "Calypso" telescope, a bore-sight mounted radiometer and satellite-based measurement of atmospheric parameters such as pressure and ozone—will be used to determine the atmospheric absorption along the line of sight to standard stars. The atmospheric transmission will be decomposed into a set of basis functions and interpolated in space in time to any position in the LSST focal plane.

This WBS will develop a pipeline for accurate spectrophotometric measurement of stars with the auxiliary telescope. We expect to repurpose and build upon publicly available code e.g. from the PFS[5] project for this purpose.

This WBS will construct the atmospheric model, which may be based either on MODTRAN (as per LSE-180) or a PCA-like decomposition of the data (suggested by [20]).

This WBS will define and develop the routine for fitting the atmospheric model to each exposure from the calibration telescope and providing estimates of the atmospheric transmission at any point in the focal plane upon request.

4.1.2.3 Detector effects An initial cross-talk correction matrix will be determined by laboratory measurements on the Camera Calibration Optical Bench (CCOB). However, to account for possibile instabilities, this WBS will develop an on-telescope method. We baseline this as being based on measurement with the CBP, but we note the alternative approach based on cosmic rays adopted by HSC [13].

Multiple reflections between the layers of the CCD give rise to spatial variability with fine scale structure in images which may vary with time [20,

[5]Subaru's Prime Focus Spectrograph; `http://sumire.ipmu.jp/pfs/`.

§2.5.1]. These can be characterized by white light flat-fields. Preliminary analysis indicates that these effects may be insignificant in LSST [23]; however, the baseline calls for a a routine developed in this WBS to analyse the flat field data and generate fringe frames on demand. This requirement may be relaxed if further analysis (outside the scope of thie WBS) demonstrates it to be unnecessary.

This WBS will develop algorithms to characterize and mitigate anomalies due to the nature of the camera's CCDs.

Note:
There's a complex inter-WBS situation here: the actual mitigation of CCD anomalies will generally be performed in SFM (WBS 02C.03.01), based on products provided by this WBS which, in turn, may rely on laboratory based research which is broadly outside the scope of DM. We baseline the work required to develop the corrective algorithms here. We consider moving it to WBS 02C.03.01 in future.

The effects we anticipate include:

- QE variation between pixels;
- Static non-uniform pixel sizes (e.g. "tree rings" [27]);
- Dynamic electric fields (e.g. "brighter-fatter" [2]);
- Time dependent effects in the camera (e.g. hot pixels, changing cross-talk coefficients);
- Charge transfer (in)efficiency (CTE).

Laboratory work required to understand these effects is outwith the scope of this WBS. In some cases, this work may establish that the impact of the effect may be neglected in LSST. The baseline plan addresses these issues through the following steps:

- Separate QE from pixel size variations[6] and model both as a function of position (and possibly time);

[6]Refer to work by Rudman.

- Learn how to account for pixel size variation over the scale of objects (e.g. by redistributing charge);
- Develop a correction for the brighter-fatter effect and develop models for any features which cannot be removed;
- Handle edge/bloom using masking or charge redistribution;
- Track defects (hot pixels);
- Handle CTE, including when interpolating over bleed trails.

4.1.2.4 Ghost catalog The Calibration Products Pipeline must provide a catalog of optical ghosts and glints which is available for use in other parts of the system. Detailed characterization of ghosts in the LSST system will only be possible when the system is operational. Our baseline design therefore calls for this system to be prototyped using data from precursor instrumentation; we note that ghosts in e.g. HSC are well known and more significant than are expected in LSST.

> **Note:**
> It is not currently clear where the responsibility for characterizing ghosts and glints in the system lies. We assume it is outwith this WBS.

4.1.3 Constituent Use Cases and Diagrams

Produce Master Fringe Exposures; Produce Master Bias Exposure; Produce Master Dark Exposure; Calculate System Bandpasses; Calculate Telescope Bandpasses; Construct Defect Map; Produce Crosstalk Correction Matrix; Produce Optical Ghost Catalog; Produce Master Pupil Ghost Exposure; Determine CCOB-derived Illumination Correction; Determine Optical Model-derived Illumination Correction; Create Master Flat-Spectrum Flat; Determine Star Raster Photometry-derived Illumination Correction; Create Master Illumination Correction; Determine Self-calibration Correction-Derived Illumination Correction; Correct Monochromatic Flats; Reduce Spectrum Exposure; Prepare Nightly Flat Exposures;

4.1.4 Prototype Implementation

While parts of the Calibration Products Pipeline have been prototyped by the LSST Calibration Group (see the LSE-180 for discussion), these have not been written using LSST Data Management software framework or coding standards. We therefore expect to transfer the know-how, and rewrite the implementation.

4.2 Photometric Calibration Pipeline (WBS 02C.03.07)

4.2.1 Key Requirements

The Photometric Calibration Pipeline is required to internally calibrate the relative photometric zero-points of every observation, enabling the Level 2 catalogs to reach the required SRD precision.

4.2.2 Baseline Design

The adopted baseline algorithm is a variant of "ubercal" [22, 25]. This baseline is described in detail in the Photometric Self Calibration Design and Prototype Document (UCAL).

4.2.3 Constituent Use Cases and Diagrams

Perform Global Photometric Calibration;

4.2.4 Prototype Implementation

Photometric Calibration Pipeline has been fully prototyped by the LSST Calibration Group to the required level of accuracy and performance (see the UCAL document for discussion).

As the prototype has not been written using LSST Data Management software framework or coding standards, we assume a non-negligible refactoring and coding effort will be needed to convert it to production code in LSST Construction.

4.3 Astrometric Calibration Pipeline (WBS 02C.03.08)

4.3.1 Key Requirements

The Astrometric Calibration Pipeline is required to calibrate the relative and absolute astrometry of the LSST survey, enabling the Level 2 catalogs to reach the required SRD precision.

4.3.2 Baseline Design

Algorithms developed for the Photometric Calibration Pipeline (WBS 02C.03.07) will be repurposed for astrometric calibration by changing the relevant functions to minimize. This pipeline will further be aided by WCS and local astrometric registration modules developed as a component of the Single Frame Processing pipeline (WBS 02C.03.01).

Gaia standard stars will be used to fix the global astrometric system. It is likely that the existence of Gaia catalogs may make a separate Astrometric Calibration Pipeline unnecessary.

4.3.3 Constituent Use Cases and Diagrams

Perform Global Astrometric Calibration;

4.3.4 Prototype Implementation

The Astrometric Calibration Pipeline has been partially prototyped by the LSST Calibration Group, but outside of LSST Data Management software framework. We expect to transfer the know-how, and rewrite the implementation.

5 Data Release Production

[**TODO:**
Update figure to reflect changes to sections in text.]

A Data Release Production is run every year (twice in the first year of operations) to produce a set of catalog and image data products derived from all observations from the beginning of the survey to the point the production began. This includes running a variant of the difference image analysis run in Alert Production, in addition to direct analysis of individual exposures and coadded images. The data products produced by a Data Release Production are summarized in table 1.

From a conceptual standpoint, data release production can be split into five groups of pipelines, executed in approximately the following order:

1. We characterize and calibrate each exposure, estimating point-spread functions, background models, and astrometric and photometric calibration solutions. This iterates between processing individual exposures independently and jointly fitting catalogs derived from multiple overlapping exposures. These steps are described more fully in section 5.1.

2. We alternately combine images and subtract them, using differences to find artifacts and time-variable sources while building coadds that produce a deeper view of the static sky. Coaddition and difference imaging is described in section 5.2.

3. After all image processing is complete, we run additional catalog-only pipelines to fill in additional object properties. Unlike previous stages, this postprocessing is not localized on the sky, as it may use statistics computed from the full data release to improve our characterization of individual objects. Postprocessing pipelines are described in section 5.6.

This conceptual ordering is an oversimplification of the actual processing flow, however; as shown in Figure 4, pipeline groups are actually interleaved.

Each pipeline in this the diagram represents a particular piece of code excuted in parallel on a specific unit of data, but pipelines may contain additional (and more complex) parallelization to further subdivide that data unit. The processing flow also includes the possibility of iteration between pipelines, indicated by cycles in the diagram. The number of iterations in each cycle will be determined (via tests on smaller productions) before the start of

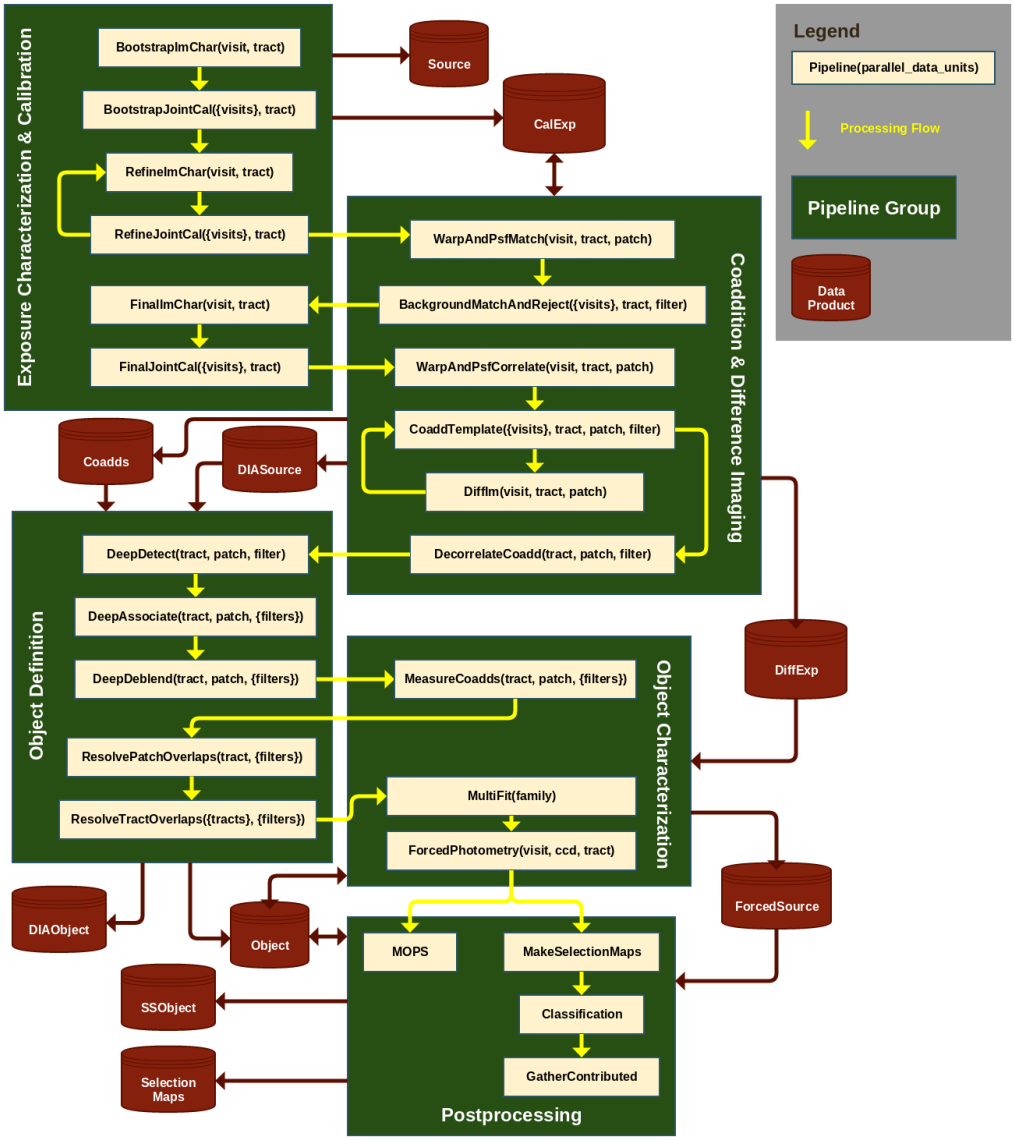


Figure 4: Summary of the Data Release Production processing flow. Processing is split into multiple pipelines, which are conceptually organized into the groups discussed in sections 5.1-5.6.

Name	Availability	Description
Source	Stored	Measurements from direct analysis of individual exposures.
DIASource	Stored	Measurements from difference imagine analysis of individual exposures.
Object	Stored	Measurements for a single astrophysical object, derived from all available information, including coadd measurements, simultaneous multi-epoch fitting, and forced photometry. Does not include solar system objects.
DIAObject	Stored	Aggregate quantities computing by associating spatially colocated DIASources.
ForcedSource	Stored	Flux measurements on each direct and difference image at the position of every Object.
SSObject	Stored	Solar system objects derived by associating DIASources and inferring their orbits.
CalExp	Regenerated	Calibrated exposure images for each CCD/visit (sum of two snaps).
DiffExp	Regenerated	Difference between CalExp and PSF-matched template coadd.
DeepCoadd	Stored	Coadd image with a reasonable combination of depth and resolution.
EpochRangeCoadd	Renegerated	Coadd image that cover only a limited range of epochs.
BestSeeingCoadd	Regenerated	Coadd image built from only the best-seeing images.
PSFMatchedCoadd	Regenerated	Coadd image with a constant, predetermined PSF.

Table 1: Table of public data products produced during a Data Release Production. A full description of these data products can be found in the Data Products Definition Document (LSE-163).

the production, allowing us to remove these cycles simply by duplicating some pipelines a fixed number of times. The final data release production processing can thus be described as a directed acyclic graph (DAG) to be executed by the orchestration middleware, with pipelines as edges and (intermediate) data products as vertices. Most of the graph will be generated by applications code before the production begins, using a format and/or API defined by the orchestration middleware. Howver, some parts of the graph must be generated on-the-fly; this will be discussed further in section 5.5.1.

5.1 Image Characterization and Calibration

[**ImChar/JointCal Diagram:**
Extract ImChar/JointCal pipelines from "DRP Top-Level Overview" on confluence and expand detail to show data flow and ordering of "Task/Process" boxes.]

The first steps in a Data Release Production characterize the properties of individual exposures, by iterating between pixel-level processing of individual visits ("ImChar", or "Image Characterization" steps) and joint fitting of all catalogs overlapping a tract ("JointCal", or "Joint Calibration" steps). All ImChar steps involve fitting the PSF model and measuring Sources (gradually improving these as we iterate), while JointCal steps fit for new astrometric (WCS) and photometric solutions while building new reference catalogs for the ImChar steps. Iteration is necessary for a few reasons:

- The PSF and WCS must have a consistent definition of object centroids. Celestial positions from a reference catalog are transformed via the WCS to set the positions of stars used to build the PSF model, but the PSF model is then used to measure debiased centroids that feed the WCS fitting.

- The later stages of photometric calibration and PSF modeling require secure star selection and colors to infer their SEDs. Magnitude and morphological measurements from ImChar stages are aggregated the reference catalog in the subsequent JointCal stage, allowing these colors and classifications to be used for PSF modeling in the following ImChar stage.

The ImChar and JointCal iteration is itself interleaved with background matching and difference imaging, as described in section 5.2. This allows

the better backgrounds and masks to be defined by comparisons between images before the final Source measurements, image characterizations, and calibrations.

Each ImChar pipeline runs on a single visit, and each JointCal pipeline runs simultaneously on all visits within a single tract, allowing tracts to be run entirely independently.

The final output data products of the ImChar/JointCal iteration are the Source table and most of the CalExp (calibrated exposure) images. CalExp is an Exposure, and hence has Image, Mask, Variance, Background, PSF, WCS, and PhotoCalib components that we will track separately.

5.1.1 BootstrapImChar

The BootstrapImChar pipeline is the first thing run on each science exposure in a data release. It has the difficult task of bootstrapping multiple quantities (PSF, WCS, photometric calibration, background model, etc.) that each normally require all of the others to be specified when one is fit. As a result, while the algorithmic components to be run in this pipeline are generally clear, their ordering and specific requirements are not; algorithms that are run early will have a harder task than algorithms that are run later, and some iteration will almost certainly be necessary.

A plausible (but by no means certain) high-level algorithm for this pipeline is given below in pseudocode. Highlighted terms are described in more detail below the pseudocode block.

```
def BootstrapImChar(raw, reference):
    # Some data products components are visit-wide and some are per-CCD;
    # these imaginary data types lets us deal with both.
    # VisitExposure also has components; most are self-explanatory, and
    # {mi} == {image,mask,variance} (for "MaskedImage").
    calexp = VisitExposure()
    sources = VisitCatalog()
    snaps = VisitMaskedImageList()  # holds both snaps, but only {image,mask,variance}
    parallel for ccd in ALL_SENSORS:
        snaps[ccd] = [RunISR(raw[ccd]) for snap in SNAP_NUMBERS]
        snaps[ccd].mask = SubtractSnaps(snaps[ccd])
        calexp[ccd].mi = CombineSnaps(snaps[ccd])
    calexp.psf = FitWavefront(calexp[WAVEFRONT_SENSORS].mi)
    calexp.{image,mask,variance,background}
        = SubtractBackground(calexp.mi)
    parallel for ccd in ALL_SENSORS:
        sources[ccd] = DetectSources(calexp.{mi,psf})
    sources[ccd] = DeblendSources(sources[ccd], calexp.{mi,psf})
    sources[ccd] = MeasureSources(sources[ccd], calexp.{mi,psf})
    matches = MatchSemiBlind(sources, reference)
    while not converged:
```

```
    SelectStars(matches, exposures)
    calexp.wcs = FitWCS(matches, sources, reference)
    calexp.psf = FitPSF(matches, sources, calexp.{mi,wcs})
    WriteDiagnostics(snaps, calexp, sources)
    parallel for ccd in ALL_SENSORS:
        snaps[ccd] = SubtractSnaps(snaps[ccd], calexp[ccd].psf)
        calexp[ccd].mi = CombineSnaps(snaps[ccd])
        calexp[ccd].mi = SubtractStars(calexp[ccd].{mi,psf}, sources[ccd])
    calexp.{mi,background} = SubtractBackground(calexp.mi)
    parallel for ccd in ALL_SENSORS:
        sources[ccd] = DetectSources(calexp.{mi,psf})
        calexp[ccd].mi, sources[ccd] =
            ReinsertStars(calexp[ccd].{mi,psf}, sources[ccd])
        sources[ccd] = DeblendSources(sources[ccd], calexp.{mi,psf})
        sources[ccd] = MeasureSources(sources[ccd], calexp.{mi,psf})
    matches = MatchNonBlind(sources, reference)
calexp.psf.apcorr = FitApCorr(matches, sources)
parallel for ccd in SCIENCE_SENSORS:
    sources[ccd] = ApplyApCorr(sources[ccd], calexp.psf)
return calexp, sources
```

5.1.1.1 Input Data Product: Raw Raw amplifier images from science and wavefront CCDs, spread across one or more snaps. Needed telescope telemetry (seeing estimate, approximate pointing) is assumed to be included in the raw image metadata.

5.1.1.2 Input Data Product: Reference A full-sky catalog of reference stars derived from both external (e.g. Gaia) and LSST data.

The StandardJointCal pipeline will later define a deeper reference catalog derived from this one and the new data being processed, but the origin and depth of the initial reference catalog is largely TBD. It will almost certainly include Gaia stars, but it may also include data from other telescopes, LSST special programs, LSST commissioning observations, and/or the last LSST data release. Decisions will require some combination of negotation with the LSST commissioning team, specification of the special programs, quality analysis and experimentation with the Gaia catalog, and policy decisions from DM leadership on the degree to which data releases are required to be independent. Depending on the choices selected, it could also require a major separate processing effort using modified versions of the data release production pipelines.

5.1.1.3 Output Data Product: Source A preliminary version of the Source table. This could contain all of the columns in the DPDD Source

schema if the MeasureSources is appropriately configured, but some of these columns are likely unnecessary in its role as an intermediate data product that feeds StandardJointCal, and it is likely that other non-DPDD columns will be present for that role.

BootstrapImChar also has the capability to produce even earlier versions of the Source table for diagnostic purposes (see WriteDiagnostics). These tables are not associated with any photometric calibration or aperture correction, and some may not have any measurements besides centroids, and hence are never substitutable for the final Source table.

5.1.1.4 Output Data Product: CalExp A preliminary version of the CalExp (calibrated direct exposure). CalExp is an Exposure object, and hence it has several components. BootstrapImChar is the only pipeline that actually updates all of them. Some CalExp components are determined at the scale of a full FoV and hence should probably be persisted at the visit level (PSF, WCS, PhotoCalib, Background), while others are straightforward CCD-level data products (Image, Mask, Variance).

5.1.1.5 RunISR Delegate to the ISR algorithmic component to perform standard detrending as well as brighter-fatter correction and interpolation for pixel-area variations (Warping Irregularly-Sampled Images). It is possible that these corrections will require a PSF model, and hence must be backed-out and recorrected at a later stage when an improved PSF model is available.

We assume that the applied flat field is appropriate for background estimation.

5.1.1.6 SubtractSnaps Delegate to the Snap Subtraction algorithmic component to mask artifacts in the difference between snaps. If passed a PSF (as in the second call), also interpolate them by delegating to the Artifact Interpolation algorithmic component.

We assume here that the PSF modeled on the combination of the two Snaps is sufficient for interpolation on the Snaps individually; if this is not true, we can just mask and interpolate both Snaps when an artifact appears on either of them (or we could do per-Snap PSF estimation, but that's a lot more work for very little gain).

5.1.1.7 CombineSnaps Delegate to the Image Coaddition algorithmic component to combine the two Snaps while handling masks appropriately.

We assume there is no warping involved in combining snaps. If this is needed, we should instead advocate for dropping snaps in favor of a a single longer exposure.

5.1.1.8 FitWavefront Delegate to the Wavefront Sensor PSF algorithmic component to generate an approximate PSF using only data from the wavefront sensors and observational metadata (e.g. reported seeing).

Processing the wavefront sensors will likely require some form of detection and measurement; we currently consider this to be part of the Wavefront Sensor PSF code, though it may delegate to e.g. Source Detection and/or Single Frame Measurement.

The required quality of this PSF estimate is TBD; setting preliminary requirements will involve running a version of BootstrapImChar with at least mature detection and PSF-modeling algorithms on precursor data taken in crowded fields, and final requirements will require proceessing full LSST camera data in crowded fields. However, robustness to poor data quality and crowding is much more important than accuracy; this stage need only provide a good enough result for subsequent stages to prcoeed.

5.1.1.9 SubtractBackground Delegate to the Background Estimation algorithmic component to model and subtract the background consistently over the full field of view.

The multiple backgrounds subtracted in BootstrapImChar may or may not be cumulative (i.e. we may or may not add the previous background back in before estimating the latest one).

5.1.1.10 DetectSources Delegate to the Source Detection algorithmic component to find above-threshold regions (Footprints) and peaks within them in a PSF-correlated version of the image.

In crowded fields, each iteration of detection will decrease the threshold, increasing the number of objects detection. Because this will treat fluctuations in the background due to undetected objects as noise, we may need to extend PSF-correlation to the appropriate filter for an image with correlated noise and characterize the noise field from the image itself.

Because we will use wavefront data to constrain the PSF, we also run detection on the wavefront sensors. It is possible that this will require a different algorithmic component if we cannot just treat the wavefront sensors as science sensors with an out-of-focus PSF.

5.1.1.11 DeblendSources Delegate to the Single Frame Deblending algorithmic component to split Footprints with multiple peaks into deblend families.

Because we will use wavefront data to constrain the PSF, we also run deblending on the wavefront sensors. It is possible that this will require a different algorithmic component if we cannot just treat the wavefront sensors as science sensors with an out-of-focus PSF, and we need deblending to extract wavefront information.

5.1.1.12 MeasureSources Delegate to the Single Frame Measurement algorithmic component to measure source properties.

In BootstrapImChar, we anticipate using the Neighbor Noise Replacement approach to deblending, with the following plugin algorithms:

- Centroids
- Second-Moment Shapes
- Pixel Flag Aggregation
- Aperture Photometry (but only for one or two radii)
- Static Point Source Models

Because we will use wavefront data to constrain the PSF, we also run measurement on the wavefront sensors (but probably without any flux measurement algorithms, and perhaps with modified versions of other algorithms). It is possible that this will require a different algorithmic component if we cannot just treat the wavefront sensors as science sensors with an out-of-focus PSF.

5.1.1.13 MatchSemiBlind Delegate to the Single Visit Reference Matching algorithmic component to match source catalogs to a global reference catalog. This occurs over the full field of view, ensuring robust matching even

when some CCDs have no matchable stars due to crowding, flux limits, or artifacts.

"Semi-Blind" refers to the fact that the WCS is not yet well known (all we have is what is provided by the observatory), so the matching algorithm must account for an unknown (but small) offset between the WCS-predicted sources positions and the reference catalog positions.

5.1.1.14 SelectStars Use reference catalog classifications and source flags to select a clean sample stars to use for later stages.

If we decide not to rely on a pre-existing reference catalog to separate stars from galaxies and other objects, we will need a new algorithmic component to select stars based on source measurements.

5.1.1.15 FitWCS Delegate to the Single Visit Astrometric Fit algorithmic component to determine the WCS of the image.

We assume this works by fitting a simple mapping from the visit's focal plane coordinate system to the sky and composing it with the (presumed fixed) mapping between CCD coordinates and focal plane coordinates. This fit will be improved in later pipelines, so it does not need to be exact; <0.05 arcsecond accuracy should be sufficient.

As we iterate in crowded fields, the number of degrees of freedom in the WCS should be allowed to slowly increase.

5.1.1.16 FitPSF Delegate to the Full Visit PSF Modeling algorithmic component to construct an improved PSF model for the image.

Because we are relying on a reference catalog to select stars, we should be able to use colors from the reference catalog to estimate SEDs an include wavelength dependence in the fit. If we do not use a the reference catalog early in BootstrapImChar, PSF estimation here will not be wavelength-dependent. In either case the PSF model will be further improved in later pipelines.

PSF estimation at this stage must include some effort to model the wings of bright stars, even if this is tracked and constrained separately from the model for the core of the PSF.

As we iterate in crowded fields, the number of degrees of freedom in the PSF model should be allowed to slowly increase.

5.1.1.17 WriteDiagnostics If desired, the current state of the `source`, `calexp`, and `snaps` variables may be persisted here for diagnostic purposes.

5.1.1.18 SubtractStars Subtract all detected stars above a flux limit from the image, using the PSF model. In crowded fields, this should allow subsequent SubtractBackground and DetectSources steps to push fainter by removing the brightest stars in the image.

Sources classified as extended are never subtracted.

5.1.1.19 ReinsertStars Add stars removed in SubtractStars back into the image, and merge corresponding Footprints and peaks into the source catalog.

5.1.1.20 MatchNonBlind Match a single-CCD source catalog to a global reference frame, probably by delegating to the same matching algorithm used in JointCal pipelines. A separate algorithm component may be needed for efficiency or code maintenance reasons; this is a simple limiting case of the multi-way JointCal matching problem that may or may not merit a separate simpler implementation.

"Non-Blind" refers to the fact that the WCS is now known well enough that there is no significant offset between WCS-projected source positions and reference catalog positions.

5.1.1.21 FitApCorr Delegate to the Aperture Correction algorithmic component to construct a curve of growth from aperture photometry measurements and build an interpolated mapping from other fluxes to the predicted integrated flux at infinity.

5.1.1.22 ApplyApCorr Delegate to the Aperture Correction algorithmic component to apply aperture corrections to flux measurements.

5.1.2 StandardJointCal

In StandardJointCal, we jointly process all of the Source tables produced by running BootstrapImChar on each visit in a tract. There are four steps:

1. We match all sources and the reference catalog by delegating to JointCalMatching. This is a non-blind search; we assume the WCSs output

by BootstrapImChar are good enough that we don't need to fit for any additional offsets between images at this stage. Some matches will not include a reference object, as the sources will almost certainly extend deeper than the reference catalog.

2. We classify matches to select a clean sample of low-variability stars for later steps, delegating to JointCalClassification. This uses morphological and possibly color information from source measurements as well as reference catalog information (where available). This step also assigns an inferred SED to each match from its colors; for matches associated with a reference object, whether this supersedes SEDs or colors in the reference catalog is depends on our approach to absolute calibration.

3. We fit simultaneously for improved astrometric solution by requiring each star in a match to have the same position. This may need to correct (perhaps approximately) for centroid shifts due to DCR and/or proper motion; if it does not, it must be robust against these shifts (perhaps via outlier rejection). The models and parameters to fit must be determined by experimentation, but they will represent further perturbation of the WCS fit in BootstrapImChar. This fit generates a new WCS component for each CalExp.

4. We fit simultaneously for photometric zeropoints by requiring each star in a match to have the same flux after applying smoothed monochromatic flat fields produced by the calibration products pipeline. There is a small chance this fit will also be used to further constrain those monochromatic flat fields. This fit generates a new PhotoCalib component for each CalExp.

In addition to updating the CalExp WCS and PhotoCalib, StandardJointCal generates a new Reference dataset containing the joint-fit centroids and fluxes for each of its match groups as well as their classifications and inferred SEDs.

StandardJointCal may be iterated with RefineImChar to ensure the PSF and WCS converge on the same centroid definitions. StandardJointCal is always run immediately after BootstrapImChar, but RefineImChar or StandardJointCal may be the last step in the iteration run before proceding with WarpAndPsfMatch.

5.1.3 RefineImChar

RefineImChar performs an incremental improvement on the measurements and PSF model produced by BootstrapImChar, using the improved reference catalog, WCS, and PhotoCalib produced by StandardJointCal. Its steps are thus a strict subset of those in BootstrapImChar. A pseudocode description of RefineImChar is given below, but all steps refer to back to the descriptions in 5.1.1:

```
def RefineImChar(calexp, sources, reference):
    matches = MatchNonBlind(sources, reference)
    SelectStars(matches, exposures)
    calexp.psf = FitPSF(matches, sources, calexp.{mi,wcs})
    parallel for ccd in ALL_SENSORS:
        calexp[ccd].mi = SubtractStars(calexp[ccd].{mi,psf}, sources[ccd])
    calexp.{mi,background} = SubtractBackground(calexp.mi)
    parallel for ccd in ALL_SENSORS:
        sources[ccd] = DetectSources(calexp.{mi,psf})
        calexp[ccd].mi, sources[ccd] =
            ReinsertStars(calexp[ccd].{mi,psf}, sources[ccd])
        sources[ccd] = DeblendSources(sources[ccd], calexp.{mi,psf})
        sources[ccd] = MeasureSources(sources[ccd], calexp.{mi,psf})
    calexp.psf.apcorr = FitApCorr(matches, sources)
    parallel for ccd in ALL_SENSORS:
        sources[ccd] = ApplyApCorr(sources[ccd], calexp.psf)
    return calexp, sources
```

This is essentially just another iteration of the loop in in BootstrapImChar, without the WCS-fitting or artifact-handling stages. We assume that we continue to process the wavefront sensors here (because we will use them in the FitPSF step), but it may be that previous processing may be sufficient.

Note that RefineImChar does not update the CalExp's WCS, PhotoCalib, Image, or Variance (and its Mask is only updated to indicate new detections).

5.1.4 FinalImChar

FinalImChar is responsible for producting the final PSF models and source measurements. While similar to RefineImChar, it is run after at least one iteration of the BackgroundMatchAndReject and possibly UpdateMasks pipelines, which provide it with the final background model and mask.

The steps in FinalImChar are identical to those in RefineImChar, with just a few exceptions:

- The background is not re-estimated and subtracted.

- The suite of plugin run by Single Frame Measurement is expanded to included all algorithms indicated in the first column of Figure 6. This should provide all measurements in the DPDD Source table description.
- We also classify sources by delegating to Single Frame Classification, to fill the final Source table's *extendedness* field. It is possible this will also be run during RefineImChar and BootstrapImChar for diagnostic purposes.

5.1.5 FinalJointCal

FinalJointCal is *almost* identical to StandardJointCal, and the details of the differences when surrounding pipelines are more mature and the approach to absolute calibration is more clear. Because it is responsible for the final photometric calibration, it may be need to perform some steps that could be omitted from StandardJointCal because they have no impact on the ImChar pipelines. This could include a role in determining the absolute photometric calibration of the survey, especially if an external catalog (e.g. Gaia) is relied upon exclusively to tie different tracts together.

There is no need for FinalJointCal to produce a new or updated Reference dataset (except for its own internal use), as subsequent steps do not need one, and the DRP-generated reference catalog used by Alert Production will be derived from the Object table.

5.2 Coaddition and Difference Imaging

The next group of pipelines in a Data Release Production consist of image coaddition and image differencing, which we use to separate the static sky from the dynamic sky in terms of both astrophysical quantities and observational quantities. This group also includes an iteration between pipelines that combine images and pipelines that subtract the combined images from each exposure. At each differencing step, we better characterize the features that are unique to a single epoch (whether artifacts, background features, or astrophysical sources); we use these characterizations to ensure the next round of coadds include only features that are common to all epochs.

The processing flow in this pipeline group again centers around incremental updates to the CalExp dataset, which are limited here to its Background and Mask component (the Image component is also updated, but only to subract

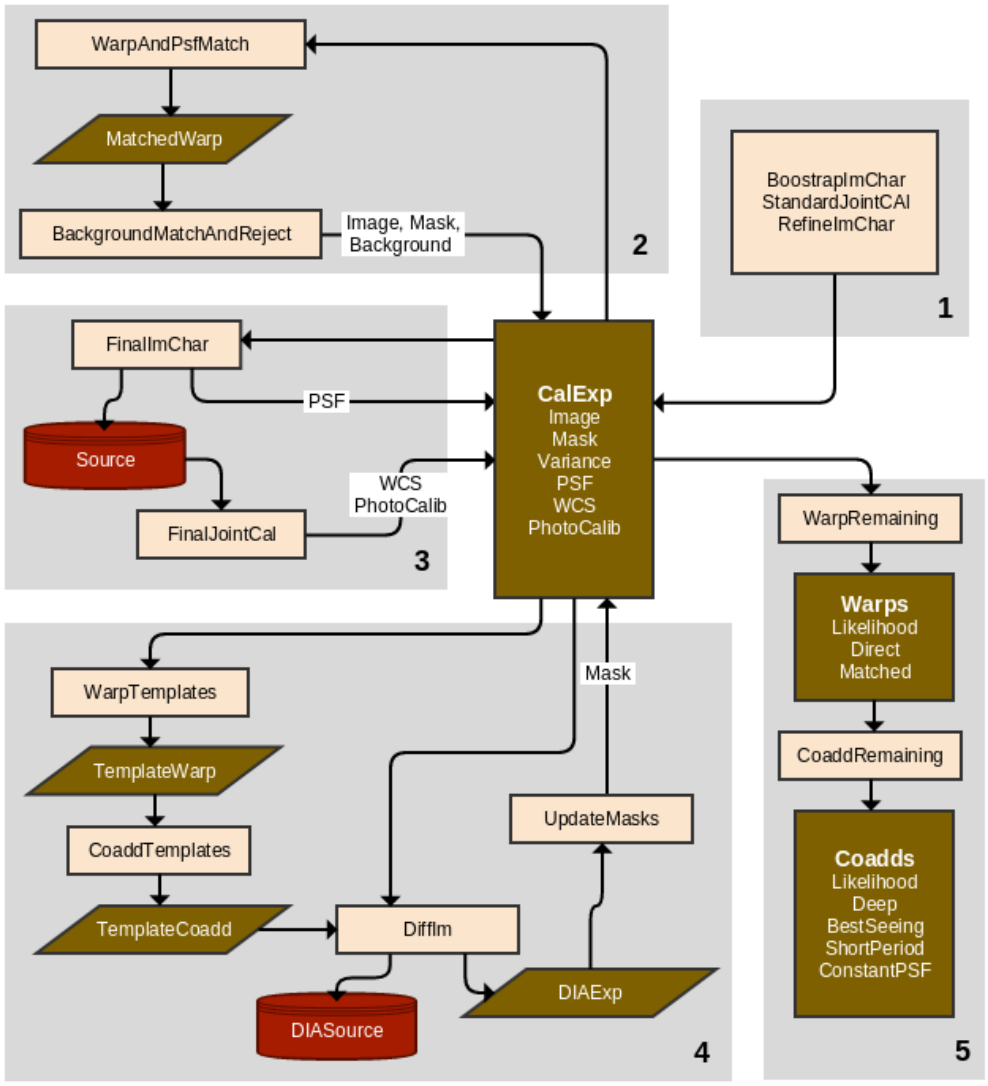


Figure 5: Data flow diagram for the Data Release Production coaddition and difference imaging pipelines. Processing proceeds roughly counterclockwise, starting from the upper right with pipelines described in Section 5.1. Each update to a component of the central CalExp dataset can in theory trigger another iteration of a previous loop, but in practice we will "unroll" these loops before production begins, yielding an acyclic graph with a series of incrementally updated CalExp datasets. The nature of this unrolling and the number of iterations will be determined by future algorithmic research. Numbered steps above are described more fully in the text.

the updated background). It will also return to the previous pipeline group described in Section 5.1 to update other CalExp components. The data flow between pipelines is shown in Figure 5, with the numbered steps are described further below:

1. The first version of the CalExp dataset is produced by running the BootstrapImChar, StandardJointCal, and RefineImChar pipelines, as described in Section 5.1.

2. We generate an updated Background and Mask via the WarpAndPsfMatch and BackgroundMatchAndReject pipelines. This produces the final CalExp Background and Image, and possibly the final Mask.

3. If the CalExp Mask has been finalized, we run the FinalImChar and FinalJointCal pipelines. These produce the final PSF, WCS, and PhotoCal. If the Mask has not been finalized, we execute at least one iteration of the next step before this one.

4. We run the WarpTemplates, CoaddTemplates, and DiffIm pipelines to generate the DIASource and DIAExp datasets. We may then be able to generate better CalExp Masks than we can obtain from BackgroundMatchAndReject by comparing the DIAExp masks across visits in the UpdateMasks pipeline.

5. After all CalExp components have been finalized, we run the WarpRemaining and CoaddRemaining to build additional coadd data products.

The baseline ordering of these steps is thus {1,2,3,4,5}, but {1,2,4,3,4,5} is perhaps just as likely, and we may ultimately require an ordering that repeats steps 2 or 3. Final decisions on the ordering and number of iteration will require testing with mature pipelines and a deep dataset taken with a realistic cadence; it is possible the configuration could even change between data releases as the survey increases in depth. Fortunately, this reconfiguring should not require significant new algorithm development.

This pipeline group is responsible for producing the following final data products:

CalExp.{Image,Background,Mask} See above.

DIAExp A CCD-level Exposure that is the difference between the CalExp and a template coadd, in the coordinate system and with the PSF of the CalExp.

DIASource A SourceCatalog containing sources detected and measured on the DIAExp images.

ConstantPSFCoadd A coadd data product (Exposure or subclass thereof) with a constant, predefined PSF.

DeepCoadd A coadd data product built to optimize depth at the possible expense of seeing.

BestSeeingCoadd A coadd data product built to optimize image quality at the possible expense of depth. Depending on the algorithm used, this may be the same as DeepCoadd.

ShortPeriodCoadd A coadd data product built from exposures in a short range of epochs, such as a year, rather than the full survey.

LikelihoodCoadd A coadd formed by correlating each image with its own PSF before combining them, used for detection and possibly building other coadds.

ShortPeriodLikelihoodCoadd Short-period likelihood coadds will also be built.

TemplateCoadd A coadd data product used for difference imaging in both DRP and AP, *or* some other tract/patch/filter data product from which the template for a given airmass can be derived.

The nature of these coadd data products depends critically on whether we are able to develop efficient algorithms for optimal coaddition, and whether these coadds are suitable for difference imaging. These algorithms are mathematically well-defined but computationally difficult; see DMTN-15 for more information. We will refer to the coadds produced by these algorithms as "decorrelated coadds"; a variant with constant PSF ("constant-PSF partially decorrelated coadd") is also possible. This choice is also mixed with the question of how we will correct for differential chromatic refraction in difference imaging; some algorithms for DCR correction involve templates that are the result of inference on input exposures rather than coaddition. There are five main scenarios for our use of decorrelated coadds:

A We use decorrelated coadds for all final coadd products. DeepCoadd and ShortPeriodCoadd will be standard decorrelated coadds with a

spatially-varying PSF, and ConstantPSFCoadd and TemplateCoadd will be constant-PSF partially-decorrelated coadds. The BestSeeingCoadd data product will be dropped, as it will be redundant with DeepCoadd. This will make coadds more expensive and complex to build, and require more algorithm development for coaddition, but will improve coadd-based measurements and make it easier to warm-start multi-epoch measurements. Difference imaging may be easier, and more visits may be usable as inputs to templates due to softened or eliminated seeing cut.

B We use decorrelated coadds for all coadds but TemplateCoadd. Measurement is still improved, and the additional computational cost of coaddition is limited to a single pipeline that is not run iteratively. Difference imaging may be harder, and the number of visits eligible for inclusion in templates may be reduced. In this scenario, we still have two options for building templates:

- **B1** Templates will be built as PSF-matched coadds, or a product of PSF-matched coadds.
- **B2** Templates are the result of inference on resampled exposures with no PSF-matching.

C We do not use decorrelated coadds at all. DeepCoadd, BestSeeingCoadd, and ShortPeriodCoadd will be direct coadds, and ConstantPSFCoadd will be a PSF-matched coadd. Coaddition will be simpler and faster, but downstream algorithms may require more sophistication, coadd measurements may be lower quality, and multi-epoch measurements may be more difficult to optimize. Here we again have the same two options for templates as option **B**:

- **C1** Templates will be built as PSF-matched coadds, or a product of PSF-matched coadds.
- **C2** Templates are the result of inference on resampled exposures with no PSF-matching.

It is also possible to combine multiple scenarios across different bands. In particular, we may not need special templates to handle DCR in redder bands, so we may select a simpler approach to dealing with them in those bands. The final selection between these options will require experiments on LSST

data or precursor data with similar DCR and seeing, though decorrelated coaddition algorithms and some approaches to DCR correction may be ruled out earlier if preliminary algorithm development does not go well.

Further differences in the pipelines themselves due to the presence or absence of decorrelated coadds will be described in the sections below.

5.2.1 WarpAndPsfMatch

This pipeline resamples and then PSF-matches CalExp images from a visit into a single patch-level image with a constant PSF. The resampling and PSF-matching can probably be accomplished separately by delegating to the Image Warping and PSF Homogenization algorithmic components, respectively. These operations can also be performed in the opposite order if the matched-to PSF is first transformed to the CalExp coordinate systems (so subsequent resampling yields a constant PSF in the coadd coordinate system). Doing PSF-matching first may be necessary (or at least easier to implement) for undersampled images.

It is possible these operations will be performed simultaneously by a new algorithmic component; this could potentially yield improved computational performance and make it easier to properly track uncertainty. These improvements are unlikely to be necessary for this pipeline, because these images and the coadds we build from them will only be used to estimate backgrounds and find artifacts, and these operations only require approximate handling of uncertainty. However, other coaddition pipelines may require building an algorithmic component capable of warping and PSF-matching simultaneously, and if that happens, we would likely use it here as well.

The only output of the WarpAndPsfMatch pipeline is the MatchedWarp Exposure intermediate data product. It contains all of the usual Exposure components, which must be propagated through the image operations as well. There is a separate MatchedWarp for each {patch, visit} combination, and these can be produced by running WarpAndPsfMatch independently on each such combination. However, individual CCD-level CalExps will be required by multiple patches, so I/O use or data transfer may be improved by running all WarpAndPsfMatch instances for a given visit together.

5.2.2 BackgroundMatchAndReject

This pipeline is responsible for generating our final estimates of the sky background and updating our artifact masks. It is one of the most algorithmically uncertain algorithms in Data Release Production, particularly from the standpoint of large-scale data flow and parallelization, because while the algorithm is well-defined and understood for a small patch of sky, we do not yet have a concrete approach for extending it to large fields containing multiple dithered images (though it has been demonstrated on SDSS data, for which the drift-scan observation strategy makes the problem simpler). It still processes tracts independently, but below that scale the parallelization is very much uncertain, and may in fact involve splitting these operations further into smaller pipelines.

The steps involved in background matching are described below. All of these operations are performed on the MatchedWarp images; these are all in the same coordinate system and have the same PSF, so they can be meaningfully added and subtracted with no additional processing.

1. We define one of the visits that overlap an area of the sky as the *reference image*. At least in the naive local specification of the algorithm, this image must be smooth and continous over the region of interest. This is done by the Build Background Reference pipeline, which must artificially (but reversibly) enforce continuity in a reference image that stitches together multiple visits to form a single-epoch-deep full tract image, unless we develop an approach for dealing with discontinuity downstream.

2. We subtract the reference image from every other visit image. This must account for any artifical features due to the construction of the reference image.

3. We run Source Detection on the per-visit difference images to find artifacts and transient sources. We do not generate a traditional catalog of these detections, as they will only be used to generate improved CalExp masks; they will likely be stored as a sequence of Footprints.

4. We estimate the background on the per-visit difference images by delegating to the Background Estimation algorithmic component. This difference background should be easier to be model than a direct image

background, as the image will be mostly free of sources and astrophysical backgrounds.

5. We build a PSF-matched coadd by adding all of the visit images (including the reference) and subtracting all of the difference image backgrounds; this yields a coadd that contains only the reference image background, which we then model and subtract by again using the Background Estimation algorithmic component. Combining the images will be performed by the Coaddition algorithmic component, which will also generate new CalExp masks by analyzing the per-pixel, multi-visit histograms of image and mask values (e.g. generalized statistical outlier rejection) to distinguish transients and artifacts from variable sources.

We are assuming in the baseline plan that we can use a matched-to PSF in WarpAndPsfMatch large enough to match all visit images to it without deconvolution. If a large marged-to PSF adversely affects subsequent processing in BackgroundMatchAndReject, we may need to develop an iterative approach in which we apply WarpAndPsfMatch only to better-seeing visits first, using a smaller target PSF, run BackgroundMatchAndReject on these, and then re-match everything to a larger target PSF and repeat with a larger set of input visits. However, this problem would suggest that the DiffIm and UpdateMasks pipelines would be even better at finding artifacts, so a more likely mitigation strategy would be to simply defer final Mask generation to after at least one iteration of those pipelines, as described in the discussion of Figure 5 at the beginning of Section 5.2.

The outputs of BackgroundMarchAndReject are updated Background and Mask components for the CalExp product. Because it is not built with the final photometric and astrometric calibration, the PSF-matched coadd built here is discarded.

5.2.3 WarpTemplates

This pipeline is responsible for generating the resampled visit-level images (TemplateWarp) used to build template coadds for difference imaging. The algorithmic content of this pipeline and the nature of its outputs depends on whether we are using decorrelated coadds (option **A**) at the beginning of 5.2), PSF-matched coadds (**B1** or **C1**), or inferring templates (**B2** or **C2**).

If we are using decorrelated coadds (option **A**), the output is equivalent to the LikelihoodWarp data product produced by the WarpRemaining pipeline

(aside from differences due to the state of the input CalExps), and the algorithm to produce it the same:

- We correlate the image with its own PSF by delegating to the Convolution Kernels software primitive.
- We resample the image by delegating to the Image Warping algorithmic component.

As with other convolution-and-warping pipelines, it is possible we will instead develop a single algorithmic component to perform both operations. These operations must include full propogation of uncertainty.

If we are not using decorrelated coadds (**B1** or **C1**), the output is equivalent to the MatchedWarp data product, and the algorithm is the same as the WarpAndPsfMatch pipeline that produces. We cannot reuse existing MatchedWarps simply because we need to utilize updated CalExps.

If we are inferring templates (**B2** or **C2**), this pipeline is only responsible for resampling, producing an output equivalent to the DirectWarp data product produced by the WarpRemaining pipeline. This work is delegated to the Image Warping algorithmic component.

5.2.4 CoaddTemplates

This pipeline generates the TemplateCoadd dataset used as the reference image for difference imaging. This may not be a simple coadd, at least in bluer bands; in order to correct for differential chromatic refraction during difference imaging, we may need to add a wavelength or airmass dimension to the usual 2-d image, making a 3-d dimensional quantity. The size of the third dimension will likely be small, however, so it should be safe to generally consider TemplateCoadd to be a small suite of coadds, in which a 2-d image is the result a different sum of or fit to the usual visit-level images (the TemplateWarp dataset, in this case).

Most of the work is done by the DCR-Corrected Template Generation algorithmic component, but its behavior depends on which of the coaddition scenarios is selected from the list at the beginning of Section 5.2):

A,B1,C1 One or more coadd-like images (corresponding to different wavelengths, airmasses, etc.) are created by delegating to the Coaddition algorithmic component to sum the TemplateWarp images with different

weights. **A only:** coadded images are then partially decorrelated to constant PSF by delegating to the Coadd Decorrelation algorithmic component.

B2,C2 The template is inferred from the resample visit images using an inverse algorithm that is yet to be developed.

5.2.5 DiffIm

In the DiffIm pipeline, we subtract a warped TemplateCoadd from each CalExp, yielding the DIAExp image, where we detect and characterize DIASources. This is quite similar to Alert Production's Alert Detection pipeline but may not be identical for several reasons. The AP variant must be optimized for low latency, and hence may avoid full-visit processing that is perfectly acceptable in DRP. In addition, the input CalExps will have been better characterized in DRP, which may make some steps taken in AP unimportant or even counterproductive. However, we expect that the algorithmic components utilized in DRP are the same as those used by AP.

The steps taken by DRP DiffIm are:

1. Retrieve the DiffIm template appropriate for the CalExps to be processed (probably handling a full visit at a time), delegating to the Template Retrieval algorithmic component. This selects the appropriate region of sky, and if necessary, collapses a higher-dimensional template dataset to a 2-d image appropriate for the CalExp's airmass.

2. (optional) Correlate the CalExp with its own PSF, delegating to the Convolution Kernel software primitive. This is the "preconvolution" approach to difference imaging, which makes PSF matching easier by performing PSF-correlation for detection first, reducing or eliminating the need for deconvolution. This approach is theoretically quite promising but still needs development.

3. Resample the template to the coordinate system of the CalExp, by delegating to the Image Warping algorithmic component.

4. Match the template's PSF to the CalExp's PSF and subtract them, by delegating to the Image Subtraction algorithmic component.

5. Run Source Detection on the difference image. We correlate the image with its PSF first using the Convolution Kernels software primitive unless this was done prior to subtraction.

6. (optional) Decorrelate the CalExp by delegating to the Difference Image Decorrelation algorithmic component.

7. Run DiffIm Measurement on the difference image to characterize difference sources. If preconvolution is used but decorrelation is not, the difference image cannot be measured using algorithms applied to standard images; alternate algorithms may be developed for some measurements, but perhaps not all.

DiffIm can probably be run entirely independently on each CCD image; this will almost certainly be taken in Alert Production. However, joint processing across a full visit may be more computationally efficient for at least some parts of template retrieval, and PSF-matching may produce better results if a more sophisticated full-visit matching algorithm is developed.

5.2.6 UpdateMasks

UpdateMasks is an optional pipeline that is only run if DIAExp masks are being used to update CalExp masks. As such, it is not run after the last iteration of DiffIm, and is never run if BackgroundMatchAndReject constructs the final CalExp masks.

Like BackgroundMatchAndReject, UpdateMasks compares the histogram of mask values at a particular spatial point to determine which masks correspond to transients (both astrophysical sources and artifacts; we want to reject both from coadds) and which correspond to variable objects. This work is delegated to Coaddition.

5.2.7 WarpRemaining

This pipeline is responsible for the full suite of resampled images used to build coadds in CoaddRemaining, after all CalExp components have been finalized. It produces some combination of the following data products, depending on the scenario(s) described at the beginning of Section 5.2:

LikelihoodWarp CalExp images are correlated with their own PSF, then resampled, via the Convolution Kernels software primitive and the

Image Warping algorithmic component. LikelihoodWarp is computed in all scenarios, but in option **C** it may not need to propogate uncertainty beyond the variance, as the resulting coadd will be used only for detection.

MatchedWarp As in WarpAndPsfMatch, CalExp images are resampled then matched to a common PSF, using Image Warping and PSF Homogenization. MatchWarp is only produced in option **C**.

DirectWarp CalExp images are simply resampled, with no further processing of the PSF, using Image Warping. MatchWarp is only produced in option **C**.

Given that all of these steps involve resampling the image, it would be desirable to do the resampling once up front, and then proceed with the PSF processing. While this is mathematically possible for all of these cases, it would signficantly complicate the PSF correlation step required for building LikelihoodWarps.

5.2.8 CoaddRemaining

In CoaddRemaining, we build the suite of coadds used for deep detection, deblending, and object characterization. This includes the Likelihood, ShortPeriodLikelihood, Deep, BestSeeing, ShortPeriod, and ConstantPSF Coadds.

The algorithms again depend on the scenarios outlined at the beginning of Section 5.2:

A,B All non-template coadds are built from LikelihoodWarps. We start by building ShortPeriodLikelihoodCoadds by simple coaddition of the LikelihoodWarps, using the Image Coaddition algorithmic component. We decorrelate these using the Coadd Decorrelation algorithmic component to produce ShortPeriodCoadds, then sum the ShortPeriodLikelihoodCoadds to produce the full LikelihoodCoadd. The full LikelihoodCoadd is then decorrelated to produce DeepCoadd and ConstantPSFCoadd.

C We generate LikelihoodCoadd and ShortPeriodLikelihoodCoadds using the same approach as above (though the accuracy requirements for uncertainty propagation are eased). ShortPeriodCoadd, DeepCoadd, and BestSeeingCoadd are then built as different combinations of DirectWarp images, again using the Image Coaddition algorithmic component. ConstantPSFCoadds are built by combining MatchedWarps.

These coadds must propagate uncertainty, PSF models (including aperture corrections), and photometric calibration (including wavelength-dependent photometric calibration), in addition to pixel values.

5.3 Coadd Processing

In comparison to the previous two pipeline groups, coadd processing is relatively simple. All pipelines operate on individual patches, and there is no large-scale iteration between pipelines. These pipelines may individually require complex parallelization at a lower level, as they will frequently have memory usage above what can be expected to fit on a single core.

5.3.1 DeepDetect

This pipeline simply runs the Source Detection algorithmic component on combinations of LikelihoodCoadds and ShortPeriodLikelihoodCoadds, then optionally performs additional preliminary characterization on related coadds. These combinations are optimized for detecting objects with different SEDs, and there are a few different scenarios for what combinations we'll produce (which are not mutually exclusive):

- We could simply detect on each per-band LikelihoodCoadds separately.
- We could build a small suite of cross-band LikelihoodCoadds corresponding to simple and artificial but approximately spanning SEDs (flat spectrums, step functions, etc.).
- We could build a large suite of cross-band LikelihoodCoadds corresponding to a library of real star, galaxy, and QSO SEDs.
- We could build a single χ^2 coadd, which is only optimal for objects the color of the sky, but may be close enough to optimal to detect a broad range of SEDs.

Any of these combinations may also be used to combine ShortPeriodLikelihoodCoadds.

We may also convolve the images further or bin them to improve our detection efficiency for extended objects.

Actual detection on these images may be done with a lower threshold than our final target threshold of 5σ, to account for loss of efficiency due using the incorrect SED or morphological filter.

The details of the suite of detection images and morphological filters is a subject requiring further algorithmic research on precursor data (or LSST/ComCam data) at full LSST depths with at least approximately the right filter set.

After detection, CoaddSources may be deblended and characterized by running the Single Frame Deblending, Single Frame Measurement, and Single Frame Classification algorithmic components on DeepCoadd and ShortPeriodCoadd combinations that correspond to the LikelihoodCoadd combinations used for detection. These characterizations (like the rest of the CoaddSource tables) will be discarded after the DeepAssociate pipeline is run, but may be necessary to inform higher-level association algorithms run there. The requirements on characterization processing in this pipeline will be set by the needs of the DeepAssociate pipeline, but we do not expect it to involve significant new code beyond what will be used by the various ImChar pipelines.

The only output of DeepDetect is the suite of CoaddSource tables (one for each detection image) containing Footprints, peaks, and characterizations necessary for association.

5.3.2 DeepAssociate

In DeepAssociate, we perform a sophisticated spatial match of all CoaddSources and DIASources, generating tables of DIAObjects, Object candidates, and SSObject detections. We do *not* include the Source table in this merge, as virtually all Sources correspond to astrophysical objects better detected in DeepDetect or DiffIm.

The baseline plan for association is to first associate DIASources into DIAObjects using the same approach used in Alert Production (i.e. the DIAObject Generation algorithmic component), then associate DIAObjects with the multiple CoaddSource tables (using the Object Generation algorithmic component). DIASources not associated into DIAObjects will be considered candidates for merging SSObjects, which will happen in the MOPS pipeline.

These association steps must be considerably more sophisticated than simple spatial matching; they must utilize the limited flux and classification information available from detection to decide whether to merge sources

detected in different contexts. This will require astrophysical models to be included in the matching algorithms at some level; for instance:

- We must be able to associate the multiple detections that correspond to high proper-motion stars into a single Object.
- We must not associate supernovae with their host galaxies, despite the fact that their positions may be essentially the same.

To meet these goals (as well as similar ones which still need to be specififed), DeepAssociate will have to generate *multiple* hypotheses for some blend families. Some of these conflicting hypotheses will be rejected by the DeepDeblend, while others may be present in the final Object catalog (flags will be used to indicate different interpretations and our most likely interpretation). This is a generalization of the simple parent/child hierarchy used to describe different blend hypotheses in the SDSS database (see Section 2.3).

It is possible that associations could be improved by doing both merge steps simultaneously (under the hypothesis that CoaddSource presence or absence could be used to improve DIASource association). This is considered a fallback option if the two-stage association procedure described above cannot be made to work adequately.

The output of the DeepAssociate pipeline is the first version of the Object table, containing a superset of all Objects that will be characterized in later pipelines.

5.3.3 DeepDeblend

This pipeline simply delegates to the Multi-Coadd Deblending algorithmic component to deblend all Objects in a particular patch, utilizing all non-likelihood coadds of that patch. This yields HeavyFootprints containing consistent deblended pixels for every object in every (non-likelihood) coadd, while rejecting as many deblend hypotheses as possible to reduce the number of hypotheses that must be subsequently measured.

While the pipeline-level code and data flow is simple, the algorithmic component is not. Not only must deblending deal with arbirarily complex superpositions of objects with unknown morphologies, it must do so consistently across bands and the epoch ranges (with different PSFs) and ensure proper handling of Objects spawned by DIASources that may not even appear in coadds. It must also parallelize this work efficiently over multiple cores; in

order to fit patch-level images for all coadds in memory, the processing of at least the largest individual blend families must themselves be parallelized. This may be done by splitting the largest blend families into smaller groups that can be processed in parallel with only a small amount of serial iteration; it may also be done by using low-level multithreading over pixels.

The output of the DeepDeblend pipeline an update to the Object table, which adds columns (mostly flags) and removes some rows from the table produced by DeepAssociate.

5.3.4 MeasureCoadds

The MeasureCoadds pipeline delegates to the Multi-Coadd Measurement algorithmic component to jointly measure all Objects on all coadds in a patch.

Like DeepDeblend, this pipeline is itself quite simple, but it delegates to a complex algorithmic component (but a simpler one than Multi-Coadd Deblending). There are three classes of open questions in how multi-coadd measurement will proceed:

- What parameters will be fit jointly across bands, and which will be fit independently? The measurement framework for multi-coadd measurement is designed to support joint fitting, but it is likely that some algorithms will simply be Single Frame Measurement or Forced Measurement plugins that are simply run independently on the DeepCoadd and/or ConstantPSFCoadd in each band. Making these decisions will require experimentation on deep precursor and simulated data.

- How will we measure blended objects? Coadd measurement will at least begin by using the HeavyFootprints produced by DeepDeblend to use the Neighbor Noise Replacement approach, but we may then use Simultaneous Fitting to generate improved warm-start parameters for MultiFit or to build models we can use as PSF-deconvolved templates to enable the Deblend Template Projection approach in MultiFit and/or ForcedPhotometry.

- How will we parallelize? As with DeepDeblend, keeping the full suite of coadds in memory will require processing at least some blend families using many cores. For algorithms that don't require joint fitting across

different coadds, this could be done by measuring each coadd independently in parallel, but the most expensive algorithms (e.g. galaxy model fitting) are likely to be the ones where we'll want to fit jointly across bands.

The output of the MeasureCoadds pipeline is an update to the Object table, which adds columns containing measured quantities.

5.4 Overlap Resolution

The two overlap resolution pipelines are together responsible for finalizing the definitions of Objects by merging redundant processing done in tract and patch overlap regions. In most cases, object definitions in the overlap region will be the same, making the problem trivial, and even when the definitions are different we can frequently resolve the problem using purely geometrical arguments. However, some difficult cases will remain, mostly relating to blend families that are defined differently on either side.

We currently assume that overlap resolution actually drops Object rows when it merges them; this will avoid redundant processing in the performance critical MultiFit pipeline. A slower but perhaps safer alternative would be to simply flag redundant Objects. This would also allow tract overlap resolution to be moved after the MultiFit and ForcedPhotometry pipelines, which would simplify large-scale parallelization and data flow by moving the first operation requiring more than one tract (ResolveTractOverlaps until after all image processing is complete.

5.4.1 ResolvePatchOverlaps

In patch overlap resolution, all contributing patches to an area (there can be between one and four) share the same pixel grid, and we furthermore expect that they will have the same coadd pixel values. This should ensure that any above-threshold pixel in one patch is also above threshold in all others, which in turn should guarantee that patches agree on the extent of each blend family (as defined by the parent Footprint).

A common pixel grid also allows us to define the overlap areas as exact rectangular regions; we consider each patch to have an inner region (which directly abuts the inner regions of neighboring patches) and an outer region (which extends into the inner regions of neighboring patches). If we consider

the case of two overlapping patches, blend families in those patches can fall into five different categories:

- If the family falls strictly within one patch's inner region, it is assigned to that patch (and the other patch's version of the family is dropped).
- If the family crosses the boundary between patch inner regions...
  - ...but is strictly within both patches' outer regions, it is assigned to the patch whose inner region includes more of the family's footprint area.
  - ...but is strictly within only one patch's outer region, it is assigned to that patch.
  - ...and is not strictly within either patch's outer region, the two families must be merged at an Object-by-Object level. The algorithm used for this procedure is yet to be developed, but will be implemented by the Blended Overlap Resolution algorithmic component.

Overlap regions with more than two patches contributing have more possibilities, but are qualitatively no different.

[**TODO:**
Add figure explaining inner and outer patch regions.]

If pixel values in patch overlap regions cannot be guaranteed to be identical, patch overlap resolution becomes significantly harder (but no harder than tract overlap resolution), because adjacent patches may disagree on the above categories to which a family belongs.

Patch overlap resolution can be run independently on every distinct overlap region that has a different set of patches contributing to it; in the limit of many patches per tract, there are three times as many overlap regions as patches (each patch has four overlap regions shared by two patches, and four overlap regions each shared by four patches).

5.4.2 ResolveTractOverlaps

Tract overlap resolution operates under the same principles as patch overlap resolution, but the fact that different tracts have different coordinate systems and subtly different pixel values makes the problem significantly more complex.

While we do not attempt to define inner and outer regions for tracts, we can still define discrete overlap regions in which the set of contributing tracts is constant (though these regions must now be defined using spherical geometry). Because tracts may differ on the extent and membership of blend families, it will be useful here to define the concept of a "blend chain": within an overlap region a families blend chain is the recursive union of all families it overlaps with in any tract that contributes to that overlap region see Figure TODO. A blend chain is thus the maximal cross-tract definition of the extent of a blend family, and hence we can use it to categorize blends in tract overlaps:

- If a blend chain is strictly contained by only one tract, all families within that chain are assigned to that tract.
- If a blend chain is strictly contained by more than one tract, all families within that chain are assigned to the tract whose center is closest to the centroid of the blend chain.
- If a blend chain is not strictly contained by any tract, all families in the chain must be merged at an Object-by-Object level. This is done by the Blended Overlap Resolution algorithmic component, after first transforming all measurements to a new coordinate system defined to minimize distortion due to projection (such as a tangent projection at the blend chain's centroid).

ResolveTractOverlaps is the first pipeline in Data Release Production to require access to processed results from more than one tract.

[**TODO:**
Add figure explaining blend chains.]

5.5 Multi-Epoch Object Characterization

The highest quality measurements for the vast majority of LSST objects will be performed by the MultiFit and ForcedPhotometry pipelines. These measurements include stellar proper motions and parallax, galaxy shapes and fluxes, and light curves for all objects. These supersede many (but not all) measurements previously made on coadds and difference images by using

deep, multi-epoch information to constrain models while fitting directly to the original CalExp (or DIAExp) images.

The difference between the two pipelines is their parallelization axis: an instance of the MultiFit pipeline processes a single Object family at a time, utilizing all of the CalExps that overlap that family as input, while ForcedPhotometry processes one CalExp or DIAExp at a time, iterating over all Objects within its bounding box. Together these three pipelines must perform three roles:

- Fit moving point source and galaxy models to all Objects, adding new columns or updating existing columns in the Object table. This requires access to all images simultaneously, so it must be done in MultiFit.
- Fit fixed-position point source models for each object (using the MultiFit-derived positions) to each DIAExp image separately, populating the ForcedSource table. This *differential forced photometry* could concievably be done in MultiFit, but will probably be more efficient to do in ForcedPhotometry.
- Fit fixed-position point source models for each object to each CalExp image separately, also populating the ForcedSource table. This *direct forced photometry* can easily be done in either pipeline, but doing it MultiFit should give us more options for dealing with blending, and it may decrease I/O costs as well.

5.5.1 MultiFit

MultiFit is the single most computationally demanding pipeline in Data Release Production, and its data flow is essentially orthogonal to that of all previous pipelines. Instead of processing flow based on data products, each MultiFit job is an Object family covering many distinct images, and hence efficient I/O will require the orchestration layer to process these jobs in an order that minimizes the number of times each image is loaded.

From the Science Pipelines side, MultiFit is implemented as two routines, mediated by the orchestration later:

- The MultiFit "launcher" processes the Object table and defines family-level MultiFit jobs, including the region of sky required and the corresponding data IDs and pixel-area regions (unless the latter two are more efficiently derived from the sky area by the orchestration layer).

- The MultiFit "fitter" processes a single Object family, accepting all required image data from the orchestration layer and returning an Object record (and possibly a table of related ForcedSources). This is the Multi-Epoch Measurement algorithmic component.

This simple picture is complicated by the presence of extremely large blend families, however. Some blend families may be large enough that a single MultiFit job could require more memory than is available on a full node (or require more cores on a node than can be utilized by lower-level parallelization). We see two possibilities for addressing this problem:

- The fitter could utilize cross-node communication to extend jobs over more nodes. The most obvious approach would give each node full responsibility for any processing a on group of full CalExps it holds in memory, as well as responsibility for "directing" a number of MultiFit jobs. These jobs would delegate pixel processing on CalExps to the nodes responsible for them (this constitutes the bulk of the processing). This would require low-latency but low-bandwidth communication; the summary information passed between the directing jobs and the CalExp-level processing jobs is much smaller than the actual CalExps or even the portion of a CalExp used by a particular fitting job, but this communication happens within a relatively tight loop (though not the innermost loop). This approach will also require structuring the algorithmic code to abstract out communication, and may require an alternate mode to run small jobs for testing.

- The launcher could define a graph of sub-family jobs that correspond to an iterative divide-and-conquer approach to large families. This approach will require more flexibilty in the algorithmic code to handle more combinations of fixed and free parameters (to deal with neighboring objects on the edges of the images being considered), more tuning and experimentation, and more sophisticated launcher code. Fitting individual large objects in this scenario could also require binning images in the orchestration or data access layer.

It is unclear which of these approaches will be more computationally expensive. The first option may reduce I/O or total network usage at the expense sensitivity to network latency. The second option may require redundant processing by forcing iterative fitting, but that sort of iterative fitting may lead to faster convergence and hence be used even in the first option.

If direct forced photometry is performed in MultiFit, moving-point source models will simply be re-fit with per-epoch amplitudes allowed to vary independently and all other parameters held fixed. The same approach could be used to perform differential forced photometry, but this would require also passing DIAExp pixel data to MultiFit.

Significant uncertainty also remains in how MultiFit will handle blending even in small families, but this decision will not have larger-scale processing impacts, and will be discussed further in Section 8.6.3.

5.5.2 ForcedPhotometry

In ForcedPhotometry, we simply measure point-source and possibly aperture photometry (the baseline is point source photometry, but aperture photometry should be implemented for diagnostic use and as a fallback) on individual CalExp or DIAExp images, using positions from the Object table.

Aside from querying the Object table for the list of Objects overlapping the image, all work is delegated to the Forced Measurement algorithmic component. The only algorithmic challenge is how to deal with blending. If only differential forced photometry is performed in this pipeline, it may be appropriate to simply fit all Objects within each family simultaneously with point source models. The other alterative is to project templates from MultiFit or possibly MeasureCoadds and replace neighbors with noise (as described in Sections 8.6.3.1 and 8.6.3.2).

5.6 Postprocessing

The pipelines in the postprocessing group may be run after nearly all image processing is complete, and with the possible exception of MakeSelectionMaps, include no image processing themselves. While we do not expect that these pipelines will require significant new algorithm development, they include some of the least well-defined aspects of Data Release Production; many of these pipelines are essentially placeholders for work that may ultimately be split out into multiple new pipelines or included in existing ones. Unlike the rest of DRP, a more detailed design here is blocked more by the lack of clear requirements and policies than a need for algorithmic research.

5.6.1 MOPS

MOPS plays essentially the same role in DRP that it plays in AP: it builds the SSObject (Solar System Object) table from DIASources that have not already been associated with DIAObjects. We will attempt to make its implementation as similar as possible to the AP DayMOPS pipeline, but the fact that DRP will run MOPS on all DIASources in the survey at once (instead of incrementally) make this impossible in details. The steps in MOPS are (with some iteration):

- Delegate to the Make Tracklets algorithmic component to combine unassociated DIASources into *tracklets*.
- Delegate to the Attribution and Precovery algorithmic component to predict the positions of known solar system objects and associate them with tracklets. The definition of a "known" solar system object cleraly depends on the input catalog; this may be an external catalog or a snapshot of the Level 1 SSObject table.
- Delegate to the Orbit Fitting algorithmic component to merge unassociated tracklets into tracks and fit orbits for SSObjects where possible.

The choice of initial catalog largely depends on the false-object rate in the Level 1 SSObject; if the only improvements in data release production are slightly improved orbit and/or new SSObjects, using the Level 1 SSObject table could dramatically speed up processing – but it may also remove the possibility of removing nonexistent objects.

[**Note:**
TODO Reference appropriate subsection of AP section.]

MOPS represents a full-survey sequence point in the production, but we expect that it will be a relatively easy one to implement, because it operates on relatively small inputs (unassociated DIASources) and produces a single new table (SSObject) as its only major output (though IDs linking DIASources and SSObjects must also be stored in either DIASource or a join table). This should mean that it can be run after most other data products have already been ingested, while requiring little temporary storage as the rest of the processing proceeds tract-by-tract.

5.6.2 ApplyCalibrations

The processing described in the previous sections produces four tables that ultimately must be ingested into the public database: Source, DIASource, Object, DIAObject, SSObject, and ForcedSource. The quantities produced by previous pipelines are in raw units, however (e.g. fluxes are in counts, positions in pixels). These must be transformed into calibrated units via our astrometric and photometric solutions, a process we delegate to the Raw Measurement Calibration algorithmic component.

This is the primary place where the wavelength-dependent photometric calibrations generated by the Calibration Product Pipelines are applied. This will require inferring an SED for every object (or source) from its measured colors. The families of SEDs and the choice of color measurements used are subjects for future algorithmic research, but it should be possible to resolve these questions with relatively little effort. The inferred SED must be recorded, allowing science users to recalibrate as desired with their own preferred SED. One possible complication here is that PSF models are also wavelength dependent, and the SED for this purpose must be inferred much earlier in the processing. Because it is highly desirable that the SEDs used for PSF-dependent measurement be the same as those used for photometric calibration, we may need to either infer SEDs early in the processing from preliminary color measurements or estimate the response of measurements to changes in PSF-evaluation SED so it can be approximately updated later.

[**Note:**
TODO Reference appropriate subsection of CPP section.]

It is currently unclear when and where calibrations will be applied; there are several options:

- We could apply calibrations to tables before ingesting them into the public database; this would logically create new calibrated versions of each table data product.
- We could apply calibrations to tables *as* we ingest them into the final database.
- We could ingest tables into the temporary tables in the database and apply the calibrations within the database.

Regardless of which option is chosen for each public table, the Raw Measurement Calibration algorithmic component will probably need to support operation both outside the database on in-memory table data and within the database (via, e.g. user-defined functions). The former will be needed to apply calibrations to intermediate data products for diagnostic purposes, while the latter will be needed to allow Level 3 users to recalibrate objects according to their own assumed SEDs.

5.6.3 MakeSelectionMaps

The MakeSelectionMaps is responsible for producing multi-scale maps that describe LSST's depth and efficiency at detecting different classes of object. The details of what metrics will be mapped, the format and scale of the maps (e.g. hierarchical pixelizations vs polygons), and the way the metrics will be computed are all unknown.

The approach must be extensible at Level 3: science users will need to build additional maps that can be utilized as efficiently by large collaborations as DM-produced maps. This will ease the pressure on DM to provide a large suite of maps, but the details of what DM will provide still needs to be clarified to the community.

One potential major risk here is that the most common way to determine accurate depth and selection metrics is to add fake sources to the data and reprocess, and this can require reprocessing each unit of order 100 times. Because the reprocessing does not need to include all processing steps (assuming the skipped steps can be adequately simulated), this should not automatically be ruled out – if the pipelines that must be repeated (e.g. DeepDetect) are significantly faster than skipped steps (such as MultiFit), the overall impact on processing could still be negligible. Regardless, the role of DM in this sort of characterization also needs to be clarified to the community.

[**Note:**
TODO Cite Balrog paper (Suchyta and Huff 2016)]

5.6.4 Classification

In its simplest realization, this pipeline computes variability summary statistics and probabilistic and/or discrete classification of each Object as a star

or galaxy; this may be extended to include other categories (e.g. QSO, supernova).

Variabiliy summary statistics are delegated to the Variability Classification algorithmic component.

Type classification is delegated to the Object Classification algorithmic component. This may utilize any combination of morphological, color, and variability/motion information, and may use spatial information such as galactic latitude as a Bayesian prior. Classifications based on only morphology will also be available.

Both variability and type classification may require "training" on the full Object and ForcedSource tables and/or similar tables derived from special program data. This represents a potential full-survey sequence point for the production.

The possible need for full-dataset processing suggests that it may be more efficient to perform classification in the final public database, in order to utilize it for large-scale aggregation calculations. This may not be feasible if final public database tables are write-once, as classification may require both read and write operations on Object. Putting the classification sequence point before ingest would then require keeping the Object data products for all tracts on disk before ingesting any of them.

Further specification of special programs (and DM plans for processing them) and algorithmic research are needed to determine whether classification actually will require a full-survey sequence point in the production.

5.6.5 GatherContributed

This pipeline is just a placeholder for any DM work associated with gathering, building, and/or validating major community-contributed data products.

In addition to data products produced by DM, a data release production also includes official products (essentially additional Object table columns) produced by the community. These include photometric redshifts and dust reddening maps. While DM's mandate does not extend to developing algorithms or code for these quantities, its responsibilities may include validation and running user code at scale. The parties responsible for producing these datasets and their relationship to DM needs to be better defined in terms of policy before a system for including community-contributed data products in a data release can be designed.

6 Services for Data Quality Analysis (SDQA)

6.1 Key Requirements

SQDA is a set of loosely coupled services intended to service LSST's quality assessement needs through all phases of Construction, Commissioning and Operations. Consumers of these services may include developers, facility staff, DAC (e.g., L3) users, and the general LSST science user community. Use of these services is intended for routine characterisation, fault detection and fault diagnosis.

- SDQA shall provide sevices for science data quality analysis of Level 1, 2, and Calibration Processing pipelines.
- SDQA shall provide services to support software development in Construction, Commissioning and Operations.
- SDQA shall provide for the visualization, analysis and monitoring capabilities needed for common science quality data analysis usecases. Its inputs may be gathered from SDQA services, the production pipelines, engineering data sources and non-LSST data sources.
- SDQA shall have the flexibility to support execution of ad-hoc (user-driven) tests and analyses of ad-hoc datasets (provided they are supported by the LSST stack) within a standard framework.
- SDQA shall support usecases involving interactive "drill-down" of QA data exposed through its visualisation interfaces.
- SDQA shall allow for notifications to be issued when monitoring quantities that exceed their permissible thresholds and/or have degraded over historical values.
- SDQA shall be able to collect and harvest the outputs and logs of execution of the production pipelines, and extract and expose metrics from these logs.
- SQDA shall make provision to store outputs that are not stored through other LSST data access services.

- SDQA should be deployable as high-reliability scalable services for production as well as allow for core data assessment functionality to be executed on a developer's local machine.
- SDQA shall be architected in a manner that would enable it to be deployable on standard cloud architectures outside of the LSST facilities.

6.2 Key Tasks for Each Level of QA

SDQA system will provide a framework that is capable of monitoring QA information at four different stages of capability and maturity:

QA Level 0 Testing and Validation of the DM sub-system in pre-commissioning

QA Level 1 Real-time data quality and system assesment during commissioning + operations (also, forensics)

QA Level 2 Quality assessment of Data Releases (also, forensics)

QA Level 3 Ability for the community to evaluate the data quality of their own analyses. These should made available as well-documented and deployable versions of core QA Level 0–2 services.

[**Figure summarising QA key tasks:**
Summary figure under construction]

The majority of the work described in this section falls under the 02C.10 WBS (Science Quality and Reliability Engineering). Exceptions are noted in the text as appropriate.

6.2.1 QA Level 0

The first step to good quality data is good quality software. The purpose of QA0 services is to enable testing of the DM software during pre-commissioning as well as validate software improvements during commissioning and operations, quantifying the software performance against known and/or expected outputs.

The core capabilities of QA 0 services are:

6.2.1.1 Continuous Integration Services

- Continuous integration services compile code to uncover syntax errors.
- Builds of references (tags, branches) can happen on a schedule, on developer request or on development events (eg merge to master)
- SDQA provides CI services on multiple reference platforms and uses OS portability testing as a way to ensure the codebase is well engineered for future use.

6.2.1.2 Test execution harness

- A test execution harness runs tests (such as data analysis unit tests) on a regular cadence (eg nightly/weekly/monthly) to allow basic functional checkout of the code. Tests can be added directly by developers and be caused to execute without manual intervention.
- Results from such tests are exposed in such a way to allow summary reports and meaningful failure notifications.

6.2.1.3 Validation Metrics Code

- During Construction, progress towards meeting DM subsystem requirements revolve around the Key Performance Metrics (KPMs) outlined in LDM-240. SDQA implements code to calculate these KPMs. Consult *reference to KPM Verification document* for a list of those metrics and how (and by whom and on what) they will be calculated.
- Additional metrics must be calculated to be met in order for the DM subsystem to demonstrate its operational readiness. The list of those metrics and how (and by whom) they will be calculated will be in *reference to DM Verification Plan CoDR document*. In terms of QA infrastructure, these metrics will not require different capabilities than the KPMs.
- Validation code will be implemented in such a way that it can run inline with normal pipeline processing on developer's laptops.

- Additional metrics may be devised during construction that are helpful to development or algorithm characterisation. SDQA will provide ways of executing that code in a similar way to KPMs, but apps developers may need to contribute the code (or at least document the algorithmic approach) to calculate those metrics.

6.2.1.4 Computational Metrics

- While the scope of this document is the scientific aspects of the pipelines, SDQA must also service non-scientific KPMs such as computational performance characterisation.
- SDQA will provide a capability to instrument the production pipelines to calculate computational performance metrics
- The computational performance metrics that SQDA calculates will be in practice surrogates for the actual computational performance in production since those will depend on the DAC architecture. The purpose of calculating those as part of SDQA is to continuously monitor relative performance to alert the developers that a regression has occured.
- SDQA can calculate modeled system performance from the surrogate computational metrics if a model is provided to it (eg from Architecture).
- A library of those instrumentations will be provided so that they can be mixed and matched to pipelines depending on the performance metric of interest.

6.2.1.5 Curated Datasets

- Part of the process for validating the software and its performance is selecting rich but targeted standardized data sets to generate directly comparable metrics between different versions of the software.
- SDQA will select and curate a combination of simulated and precursor datasets that are modest enough for "canary" test runs but rich enough to characterise the envelope of algorithmic performance.
- SDQA will "publish" (make available) these datasets so developers can run the validation tests directly against them in their own environments.

6.2.1.6 SQUASH - Science Quality Analysis Harness SQUASH is a QA-as-a-service architecture that comprises of the following elements:

1. The execution of simple pipeline workflows for the purposes of QA
2. The construction of those QA workflows with an emphasis on usability (as opposed to performance)
3. The collection and exposure of the results of those runs for further retrieval and analysis
4. A monitoring system to detect threshold trespass and excursions from past trends
5. Exposure of the data for retrieval and to interactive analysis tooling

Notes:

- As construction progresses, first-party DM systems to underwrite the functions of SQUASH will become production ready. In the meantime, basic implementations of minimum viable functionality may be done with boostrap or off-the-shelf solutions either as an interim measure or, in some cases, a more lightweight solution.
- A simple example of a "factory" analysis based on SQUASH is "Calculate the astrometric repeatability on this dataset; display the trend; drill down to to show the historgram of the points that went into calculating this trend".
- An advanced example of a bespoke analysis based on SQUASH is "Display a three-color diagram of the sources in this run; compute the width of point sources in the selected – e.g., blue – part of the locus"
- SQUASH will likely expose results to the LSST Science User Interface for advanced interaction scenarios (both because of the SUI team's front-end expertise but also because they are likely to be similar to science-driven interactions in intent and in execution)

6.2.2 QA Level 1

QA-1 designates the capability to assess data quality in real-time observing modes such as integration, commissioning and operations; if the role of QA-0 is to validate the software, the role of QA-1 is to validate the performance of the facility.

There are two distinct aspects to this capability:

1. Some metric products and services serve standalone user-driven use cases as in QA-0 but with additional data sources, such as the Engineering Facilities Database (EFD), and with real LSST data as opposed to simulated data or pre-cursor data sets. An example use case is "Show the width of point sources on data taken this week in windy conditions with all vents closed versus only the vents in the wind direction as a function of wind speed".

2. Some metric products are produced as part of the routine opreational processing for Level 1 and Calibration pipelines. These will predominantly use the production DM architecture at the DAC and produce metric products either through QA-specific steps in the processing or via the outputs of task instrumentation. An example use case is "show the running **XYZ**"

In the first case the architecture is based on components re-used from QA-0 (with modifications made if made necessary by more stringent performance concerns). Additional out-of-scope (for DM) work may be funded by the Commissioning WBS to support "quick-look" or "comfort display" scenarios where some facility health data is gathered directly from Telescope & Site systems, in which case a component will be added to the QA-0 architecture to support this.

In the second case, the Level 1 DM system software and processing infrastructure at the DAC is used. The Data Access framework (DAX) is used to access all data including values from the EFD and Calibration products.

Note that the EFD is specified to hold all telemetry generated by any observatory system.

All QA-0 components will be involved in QA-1 workflows. The following additional components originate from QA-1 requirements:

6.2.2.1 Alert QA There are two QA components developed for Alert Production:

- A static analysis component that can check, for example, whether the alerts conform to a valid format. This kind of component can be incorporated in the normal Alert Production pipeline.
- A component to receive alerts (akin to a mini-broker) and collect statistics on received events. This would run as a canary node outside LSST facilities to test the alert system is functioning correctly.

6.2.2.2 Validation Metrics Performance As noted, the components of QA-0 to devise key metrics are qualititatively suitable for QA-1. However:

- We expect to make some optimizations to allow them not to consume a significant portion of the 60-second alert time budget.
- In the area of computational performance metrics, additional metrics or instrumentations could be needed due to specific elements of the data center architecture, which at this point is still under design. These will be provided under the Processing Control and Site Infrastructure WBS (02C.07)

6.2.2.3 Dome / Operator Displays Some QA displays may be useful as "comfort displays" (or "facility heartbeats") to staff on site at the telescope, or remote operators. These may require interfaces to data that within the DM system is handled by Data Access Services. If that is the case, this work will be provided from a non-DM (Commissioning) WBS.

6.2.2.4 Telescope Systems Outputs of the SQQA system may be required by the Observatory Control System in order to take some automated action (e.g., reschedule a field). An API will be provided if there is a requirement not already covered by Data Access Services, or DAX may need to be extended to support that access (in the latter case, out of the (02C.06 WBS))

6.2.2.5 Camera Calibration The SDAQ system will also provide QA of Calibration images and products.

- Images taken from the Camera will require "prompt QA" that will run in the quasi-real-time image processing system. Camera is interested in the monitoring infrastructure of SDQA for tracking parameters such as read noice, cross-talk, linearity etc.
- QA of Calibration Products Production data products (i.e., master calibration images and calibration database entries). These are similar in architecture and implementation to other DRP-related tests
- The one exception to the above is the daily daytime/twilight calibration operations prior to night-time observing. QA done for this calibration sequence needs to run under Obsetvatory Control System. There is therefore an explicit or perhaps implicit interface to the OCS that is yet to be specified.

  [I am still unclear as to whether these are all the calibrations we are talking about - I get the dome flats, what about things produced by the spectrometer, the data reconstituted from the lasers etc? - FE]

6.2.2.6 Engineering and Commissioning Some data that is taken specifically for engineering or commissioning purposes will require custom treatment (e.g., an image that is taken with deliberately defocussed optics should not trigger QA alarm and instead should have the noted characteristics of the defocussed sources analysed). While architecturally these are the same as other QA tests, the scope and work for this will be defined as part of the Systems Engineering WBS.

6.2.3 QA2

QA-2 designates the capability to assess the periodic Data Release Products that will be published by LSST. The key aspects that will add on to QA-1 capabilities are (1) the ability to quickly analyze and inspect large data sets; (2) identify failure modes (excursions from expectation or specification) that are rare in QA-0 analysis or real-time QA-1 processing, but represent an identifiable and systematic population or effect on the scale of a full Data Release; and (3) closely interface with calibration efforts in support of the stringent relative color calibration requirements.

In brief, the main focus of QA2 will be to (1) assess the quality of data releases (including the co-added image data products); (2) perform quality

assessment for astrometric and photometric calibration and derived products; (3) and look for problems with the image processing pipelines and systematic problems with the instrument.

In addition to the components provided in QA-0, and QA-1, the new components for QA-2 are:

6.2.3.1 DRP-specific dataset

- The scale of a DRP will impose additional performance requirements on the calculation of key performance metrics and associated quality metrics
- The need to drill down with random access to the entire DRP data set will fully exercise the SUIT capabilities.

6.2.3.2 Release data product editing tools (including provenance tracking) Understanding, assuring, and investigating data quality issues will require tight tracking of provenance tracking, particularly as different post-pixel-processing modules may be swapped for each other: e.g., photometric calibration calculations, references catalogs, etc.

6.2.3.3 Interfaces to Workflow and Provenance System(s) If the SDQA system determines that a data (whether science or calibration) is defective, it provides all the information required for the worflow system to take action on this information.

A simple example of this is that a calibration is bad, and it needs to be marked as such so that it is not used in further DRM processing - or a data frame is bad and the compute time should not be wasted processing it further for AP.

A more complex implementation is that a data product previously thought to be good is on futher processing or new tests determined to be bad. In this case will be combined with provenance information to mark *all* data polluted with the bad frame as bad, and provide sufficient information to the workflow system to allow it to trigger the necessary reprocessing with that data excluded.

These are implemented in a manner that is agnostic as to the implementation of the Workflow (e.g., they are values in a database table or API methods that different workflow systems can utilize).

In order to support the interface to the provenance system it would be useful to have some provenance analysis tools, that will allow an operator to query speficially what data went into a particular data product or used a specific data product. These would be very useful to QA but will be provided by the Data Access Services WBS (02C.06).

6.2.3.4 Output Interface to Science Pipelines

- Output interface to Science Pipelines, including from QA database

QA results may provide key feedback to model and parameter choices in the Science Pipelines. The result of the QA system should be made available to the Science Pipelines processing in clearly-tracked analysis and provenance.

6.2.3.5 Comparison tools for overlap areas due to satellite processing Data Release Processing may be distributed across multiple geographic data centers. It is important to verify consistency of the results across these data centers by analyzing both subsets of the overall data processing that are analyzed redundantly by each data center. It will be of particularly importance to test the overlap regions. A framework to define the splits and overlap region and a coherent dashboard and QA configuration to analyze these overlap regions will be key in building confidence in the merged Data Release.

6.2.3.6 Metrics/products for science users to understand quality of science data products (depth mask/selection function, etc.) The Data Release Processing should generate statistics of depth, typical seeing, etc. for regions of the sky; as well as selection functions for the sensitivity to various types of objects. These data products will need to be validated by processing of well-understood data.

6.2.3.7 Characterization report for Data Release

- Each Data Release will be accompanied by a detailed description of its key data statistics, coverage, and quality metrics.
- In addition to static summary numbers and plots, this summary may involve and interactive components. E.g., 10,000 individual is not particularly useful, but an interface to generate plots of interest based

on informed ideas of things to check will be very useful. These interactive components would be the same as those used in the validation of the data release.

6.2.4 QA3

Data quality based on science analysis performed by the LSST Science Collaborations and the community. Level 0-2 visualization and data exploration tools will be made available to the community. Make all results from the above available. Make all of the above components available to some part of the community (could be just affiliated data centers or could be individual scientists) as a supported product. Ingest external science analysis data as Level 3 data products; ingest useful external science analysis tools.

6.2.5 Interactive Visualisation

For QA to happen effectively, before it can be captured to be performed by systems it must be done by humans; the requirements of a QA system do not include all the requirements of a QA Analyst.

Interactive visualisation and free-form data exploration are critical parts of scientific and engineering insight, and for a system the size of LSST it cannot be effectively done on a developer's laptop and/or using traditional tooling. It follows that for the QA process to happen effectively, custom tooling will be necessary to support discovery workflows.

The design of these workflows is out of scope for the this document, which is focused on pipelines generating the products defined in the Data Products Definition Document and the design is described in a document under preparation. But briefly, they fall into three categories:

1. Capabilities that involve structure pre-defined high-semantics displays (e.g., dashboards) with fixed drill-down workflows. These will be serviced by the QA system, specifically the Science Quality Analysis Harness interactive dashboards.

2. Capabilities that are similar to science-user workflows in that they involve generic free-form exploration of the dataset. These will be serviced through the Science User Interface through the Science User Interface Data Analysis and Visualization Tools WBS (02C.05.02), with the Data Access services acting as interface between the SUI and SDAQ.

This is partly to leverage the superior features of the SUI system, and partly to encourage early in-house testing of the SUI features.

3. A more complex case is the situation where curated pre-defined display is desired, but free-form generic exploration of the results is required. In this situation, SDQA will have an API or facility for exporting the former into a tool suitable for the latter. One example of this would be a QA report on, say, a standardised KPM measurement that is produced as a Jupyter Notebook; the user can inspect it, or take it and further interact with the results. Further design is underway in this area.

4. In some cases specific algorithms need to be implemented to drive required visualisation scenarios; these are provided as part of the Alert Production (02C.03) Or Data Release Production (02C.04) as appropriate. An example of this is N-way matching across multiple visits (9.15.8)

6.2.6 Who validates the validator?

It should be apparent from the above that the QA sevices, while not a critical component in operational terms, nevertheless comprise a system of high semantic value to multiple audiences - dome operators, software developers, science operations staff, data release production engineers and science consumers. Therefore care must be taken to design into the system sanity self-checks to ensure the reliability of its own resuls as well as its upstream pipelines. This section outlines some of the planned features in this area:

6.2.6.1 Intrinsic design features Many of the features described so far provide an alert path for misbehaviours of the QA system. For example a trending excursion for a specific key performance metric could either be due to an algorithmic error or a validation code error. Either way, detection will be a necessary first step to investigation.

6.2.6.2 Known Truth While it may be a matter of debate as to how accurate construction-era simulations are compared to the eventual on-sky data, they are extremely valuable as a fixed source of "known truth" which allow for algorithmically simple QA tests that result in quantifiable performance.

6.2.6.3 Reference Truth [Someone like Z should sign off on this] Comm Cam may allow us to early on develop a small library of representative "reference fields" (eg at different galactic latitudes or ecliptic planes) to provide a minimal standard dataset against which competing algorithmic approaches can be compared (this is similar to the approach taken in Construction with percursor datasets). There would be made available outside the project too alloweing groups working on alternative algoritms and/or implementations to compare their results with the "factory" reductions. Finally, the possibility exists that these reference fields could be unencumbered by proprietary periods so that scientific groups without data rights (and perhaps not even interested in LSST per se) could also utilise them for algorithmic and/or software development.

7 Science User Interface and Toolkit

7.1 Science Pipeline Toolkit (WBS 02C.01.02.03)

7.1.1 Key Requirements

The Science Pipeline Toolkit shall provide the software components, services, and documentation required to construct Level 3 science pipelines out of components built for Level 1 and 2 pipelines. These pipelines shall be executable on LSST computing resources or elsewhere.

7.1.2 Baseline Design

The baseline design assumes that Level 3 pipelines will use the same `Tasks` infrastructure (see the Data Management Middleware Design document; DMMD) as Level 1 and 2 pipelines[7]. Therefore, Level 3 pipelines will largely be automatically constructible as a byproduct of the overall design.

The additional features unique to Level 3 involve the services to upload/-download data to/from the LSST Data Access Center. The baseline for these is to build them on community standards (VOSpace).

7.1.3 Constituent Use Cases and Diagrams

Configure Pipeline Execution; Execute Pipeline; Incorporate User Code into Pipeline; Monitor Pipeline Execution; Science Pipeline Toolkit; Select Data to be Processed; Select Data to be Stored;

7.1.4 Prototype Implementation

While no explicit prototype implementation exists at this time, the majority of LSST pipeline prototypes have successfully been designed in modular and portable fashion. This has allowed a diverse set of users to customize and run the pipelines on platforms ranging from OS X laptops, to 10,000+ core clusters (e.g., BlueWaters), and to implement plugin algorithms (e.g., Kron photometry).

[7]Another way of looking at this is that, functionally, there will be no fundamental difference between Level 2 and 3 pipelines, except for the level of privileges and access to software or hardware resources.

8 Algorithmic Components

8.1 Instrument Signature Removal

AUTHOR: Merlin

- Mask defects and saturation
- Assembly
- Overscan
- Linearity
- Crosstalk
- Full frame corrections: Dark, Flats (includes fringing)
- Pixel level corrections: Brighter fatter, static pixel size effects
- Interpolation of defects and saturation
- CR rejection
- Generate snap difference
- Snap combination

8.1.1 AP: just skip some steps?

AUTHOR: Simon

- Indicate steps to be done by camera
- call out other steps that are omitted/modified relative to the DRP version

8.1.2 DRP: do all the steps

AUTHOR: Merlin

8.2 Artifact Detection

8.2.1 Single-Exposure Morphology

8.2.1.1 Cosmic Ray Identification Cosmic rays will be identified using a Laplacian edge detection algorithm [**?**]. Laplacian edge detection involves convolving the image (I) with a smoothing function (f) tuned to the size of the expected edge width.

$$L = \bigtriangledown^2 f * I$$

In the case of cosmic rays, this implies a very sharp edge. A natural choice is a Gaussian with small σ. The discrete kernel chosen in [**?**] is

$$\bigtriangledown^2 = \frac{1}{4}\begin{pmatrix} 0 & -1 & 0 \\ -1 & 4 & -1 \\ 0 & -1 & 0 \end{pmatrix} \tag{1}$$

If just used on the native image, this filter would attenuate the signal from CRs that effect multiple adjacent pixels. So, the image is subsampled by some factor f_s. The before downsampling to the native resolution, the negative pixel values are clamped to zero. The resultant image in native pixelization will be referred to as L^+.

We construct a SNR image by dividing the Laplacian image by the noise in the image and adjusting by the subsampling factor.

$$S = \frac{L^+}{f_s N}$$

This CR detection image can be cleaned further by removing extended sources using a median filter. M_n is the median over a $n \times n$ box.

$$S' = (S * M_5)$$

If the PSF is well sampled, this SNR image can be used to detect the CRs by simply drawing a threshold in SNR. If the PSF is undersampled, the author uses the assumption that undersampled point sources are more symmetric than CRs. By constructing a "fine-structure" image, one can plase a minimum contrast between the Laplacian image and the fine structure image that further improves differentiation between CRs and point sources.

$$F = (M_3 * I) - [(M_3 * I) * M_7]$$

So the final CR selection criteria are: $S' > \sigma_{lim}$ and $L^+/F > F_{lim}$. The tuning parameters are: f_s the subsampling rate, σ_{lim} the SNR of the CRs in the detection image, f_{lim} the minimum contrast relative to the "fine-structure" image.

Add to SFM section:
We can use something like L.A.COSMIC (or CRBLASTER) but if it is too slow, we can fall back to the SDSS algorithm which does a similar thing, but does no convolutions. We should also consider why we do not use a Canny algorithm instead.

8.2.1.2 Optical ghosts We will have a set of optical ghost models. Some of these will be models of stationary ghosts (e.g. pupil ghost). Others will be a set of ghosts produced by point sources as a function of source position and brightness. The latter will likely be modeled using tools like ZEMAX or measured using projectors.

The stationary ghosts will need to be fit for since they will depend on the total light through the pupil rather than on the brightness of a given source and we do not expect to have the data necessary to compute the total flux over the focalplane in a single thread in the alert production processing. Using the fit to stationary models S and the predictions of the single source ghosts, P, we will constructy a ghost image

$$I_g = \Sigma_i S_i + \sigma_j P_j$$

where i runs over the stationary ghost models and j runs over the sources contributing to single source ghosts. We can then correct the image by:

$$I' = I - I_g$$

dependence on PSF:
The CR rejection algorithm does not depend on the PSF of the image. The single source ghosts may be a function of the PSF, but not very strongly I don't think.

8.2.2 Single-Exposure Aggregation

8.2.2.1 Linear feature detection and removal Satellite trails, out of focus airplanes, and meteors all cause long linear features in astronomical images. The Hough Transform [**?**] is a common tool used in computer vison applications to detect linear features. Linear features are parameterized by r, the perpendicular distance to the line from the origin and θ, the the angle of r with the x-axis. The (r, θ) space is binned and each pixel in the image adds its flux to all the bins consistent with that pixel location. For bright linear features, the bin at the true location of the feature will fill up because more than one bright pixel is contributing to that location in parameter space. After all pixels have been polled, the highest bins correspond to the linear features in the image.

This works very well in high signal-to-noise images, but is very computationally expensive. It is also susceptible to bright point sources overwhelming faint linear features.

An algorithm that takes care of both of these issues is presented in [**?**]. We will use this as our baseline. First the image is rescaled to bring out faint features. Next an edge detectionalgorithm is run on the image. The reference implementation uses a Canny algorithm [**?**]. This algorithm produces a set of edges that can then be mined for linear features. They use a probababalistic Hough Transforms [**?**] to cut down on computational costs. The probabalistic version limits the number of pixels that vote. This results in a list of line segments. The segments are binned in angle and any sement that is outside some tolorance of the mode is culled. This cleaned set of segments is fed to the masking algorithm.

The masking algorithm traverses each line segment found in the previous step by selecting a subregion around the segment and flattening the subregion. A weighted mean of the subregion is computed and any pixels above some threshold are considered part of the trail and masked. The subregion is moved along the segment until the end is reached. This is repeated for every segment.

One of the assumptions of the algorithm is that the trail crosses the whole image. I don't think we want to make that assumption. I also don't know why they run a Canny algorithm first and then do a Hough Transform. I guess it does the same sort of regularization that Steve tried to do with his moments.

Bickerton writeup:
Note that there is a writeup by Steve Bickerton on a different way to modify the Hough Transform to find satelite trails and it has been tried on HSC, but the paper is not complete. Thus, I didn't use it as the baseline here. The writeup is linked from DM-5872.

8.2.3 Snap Subtraction

8.2.3.1 Improvements by using multiple snaps **Cosmic Rays** We will need to still run some sort of topological identifier like the one outlined above. This is because there will be real transients and we still only want to pick out the sharp features as CRs. It will help to have less crowding, so we should do CR rejection on the snap difference if we have it.

Ghosts Snap differences will not help with ghosting as the ghosts should difference almost perfectly.

Linear features Snap differences will provide significant leverage for masking linear features. Since each segment will appear in at most one snap we can mask based on the pixels marked as detected in the difference images that are part of the trail. This will help in crowded regions. This technique will require running some sort of trail detection algorithm, but the requirements will be less stringent since the image will be so much less crowded.

8.2.4 Warped Image Comparison

AUTHOR: Jim

- Find more optical artifacts by looking at differences between warped images (this is run during background matching).
- Find transient astronomical sources we don't want to include in coadds.

8.3 Artifact Interpolation

AUTHOR: Jim

- Set mask planes for all artifacts.

- Eliminate small artifacts by interpolating them.
- Uses PSF model as interpolant.

8.4 Source Detection

AUTHOR: Jim

- Detect above-threshold regions and peaks in direct or difference images.
- Needs to work on preconvolved and unconvolved images.
- May need multi-pass variants: detect bright objects first, then faint; detect with approximate PSF, then improved.
- Need to work on wavefront sensors (with out-of-focus PSFs)

8.5 Deblending

AUTHOR: Jim

For templates, try:

- symmetry ansatz with additional regularization
- simultaenous fit of galaxy models
- spline-based models with regularization?
- (multi-coadd only) optimize color uniformity

Will be especially challenging in crowded fields, but it needs to work in that regime as well.

8.5.1 Single Frame Deblending

- Generate HeavyFootprint deblends using only a single image.
- May need to be able to work with approximate/guess PSF, even in crowded fields, if we need to deblend before PSF estimation in DRP.
- May need to work on wavefront sensors (with out-of-focus PSFs)

Figure 6: Matrix showing combinations of measurement variants, algorithms, and deblending approaches that will be implemented.

8.5.2 Multi-Coadd Deblending

- Generate consistent HeavyFootprint deblends from coadds over multiple bands and possibly epoch ranges.

8.6 Measurement

AUTHOR: Jim

8.6.1 Variants

Measurement is run in several contexts, but always consists of running an ordered list of algorithm plugins on either individual objects or families thereof. Each context corresponds to different variant of the measurement driver code,

and has a different set of plugin algorithms and approaches to measuring blended objects.

8.6.1.1 Single Frame Measurement: Measure a direct single-visit CCD image, assuming deblend information already exists and can be used to replace neighbors with noise (see 8.6.3.2).

Single Frame Measurement is run in both AP's Single Frame Processing pipeline) and DRP's BootstrapImChar, RefineImChar, and FinalImChar. It must be capable of running on wavefront sensor images, though this may require different plugin algorithms.

The driver for Single Frame Measurement is passed an input/output SourceCatalog and an Exposure to measure. Plugins take an input/output SourceRecord and an Exposure containing only the object to be measured.

8.6.1.2 Multi-Coadd Measurement: Simultaneously measure a suite of coadds representing different bandpasses, epoch ranges, and flavors. This is run only in DRP's MeasureCoadds pipeline.

The driver for Multi-Coadd Measurement is passed an input/output ObjectCatalog and a dict of Exposures to be measured. Plugins take an input/output ObjectRecord and a dict of Exposures, each containing only the object to be measured. Some plugins will also support simultanous measurement of multiple objects, which requires they be provided the subset of the ObjectCatalog to be measured and a dict of Exposures containing just those objects.

8.6.1.3 Difference Image Measurement: Measure a difference image, potentially using the associated direct image as well. Difference image measurement is run in AP's Alert Detection pipeline and DRP's DiffIm pipeline.

The signatures of difference image measurement's drivers and algorithms are at least somewhat TBD; they will take at least a difference image Exposures and a SourceCatalog/SourceRecord, but some plugins such as dipole measurement may require access to a direct image as well. Because difference imaging dramatically reduces blending, difference image measurement may require any approach to blended measurement (though any use of the associated direct image would require deblending).

If preconvolution is used to construct difference images, but they are not subsequently decorrelated, the algorithms run in difference image measurement cannot be implemented in the same way as those run in other measurement variants, and algorithms that cannot be expressed as a PSF-convolved model fit (such as second-moment shapes and all aperture fluxes) either cannot be implemented or require local decorrelation.

8.6.1.4 Multi-Epoch Measurement: Measure multiple direct images simultaneously by fitting the same WCS-transformed, PSF-convolved model to them. Blended objects in Multi-Epoch Measurement will be handled by *at least* fitting them simutaneously (8.6.3.3), which may in turn require hybrid galaxy/star models (8.6.3.4). These models may then be used as templates for deblending and replace-with-noise (8.6.3.2) measurement if this improves the results.

Because the memory and I/O requirements for multi-epoch measurement of a single object or blend family are substantial, we will not provide a driver that accepts an ObjectCatalog and measures all objects within it; instead, the peline will submit individual family-level jobs directly to the orchestration layer. The multi-epoch measurement driver will thus just operate on one blend family at a time, and manage blending while executing its plugin algorithms.

Multi-epoch measurement for DRP only includes two plugin algorithms, so it is tempting to simply hard-code these into the driver itself, but this driver will also need to support new plugins in Level 3.

Multi-epoch measurement will also be responsible for actually performing forced photometry on direct images, which it can do by holding non-amplitude parameters for moving point-source models fixed and adding a new amplitude parameter for each observation.

8.6.1.5 Forced Measurement: Measure photometry on an image using positions and shapes from an existing catalog.

In the baseline plan, we assume that forced measurement will only be run on difference images; while forced photometry on direct images will also be performed in DRP, this will be done by multi-epoch measurement.

Because difference imaging reducing blending substantially, forced measurement may not require any special handling of blends. If it does, simultaneous fitting (with point-source models) should be sufficient.

The driver for Forced Measurement is passed an input/output Source-

Catalog, an additional input ReferenceCatalog, and an Exposure to measure. Plugins take an input/output SourceRecord, an input ReferenceRecord and an Exposure. If simultaneous fitting is needed to measure blends, plugins will instead receive subsets of the catalogs passed to the driver instead of individual records.

Forced measurement is used by the DRP ForcedPhotometry pipeline and numerous pipelines in AP.

TODO:
Add references to specific AP pipelines that will use forced measurement.

8.6.2 Algorithms

8.6.2.1 Centroids

- should be equivalent to PSF model fit for stars
- use larger weight function (TBD) for extended objects
- need variant that doesn't require a PSF model (or can work with a poor guess) to run before PSF estimation.
- need to have a version (possibly the main version) that works on wavefront sensors

8.6.2.2 Pixel Flag Aggregation

- Compute summary statistics of masked pixels in the neighborhood of the source/object.

8.6.2.3 Second-Moment Shapes

- probably adaptive elliptical Gaussian weights, with fall back to unweightd, PSF-weighted, or some fixed Gaussian
- add regularization for unresolved objects - avoid crazy ellipticities for objects much smaller than PSF
- Should also compute moments of PSF model.
- Need to have a version (possibly the main version) that works on wavefront sensors to characterize the donut-like out-of-focus sources.

8.6.2.4 Aperture Photometry

- Aperture fluxes are computed by summing the total flux within an elliptical region defined on the image.
- Aperture fluxes are computed at a series of logarithmically spaced aperture sizes. Per the DPDD, the total number of apertures will vary depending on the size of the source.
- When computing fluxes for small apertures—for configurable values of "small"–we use sinc interpolation [5]. For large apertures, we use a naive summation of pixel values.
- May need to change ellipticity as a function of aperture radius.
- If run before PSF estimation, will need a variant that does not rely on the PSF model to choose aperture size/ellipticity.

8.6.2.5 Static Point Source Models

- Fit PSF model for flux only (hold center fixed at centroid or reference value)
- Doesn't use per-pixel variances for flux measurement, but might also provide measurement with per-pixel variances (for diagnostics?)

8.6.2.6 Kron Photometry

- Compute Kron radius (hard to make this robust)
- Compute flux in elliptical aperture at Kron radius.

8.6.2.7 Petrosian Photometry

- Compute Petrosian radius. Harder than it seems due to need for improvements to splines? (ask RHL)
- Compute flux in elliptical aperture at Petrosian radius.

8.6.2.8 Galaxy Models

- Some sort of bulge+disk model. Lots of need for experimentation.
- Will Monte Carlo sample in MultiFit (and maybe on coadds, too, if that helps).
- May also fit to PSF-matched coadds for consistent colors.
- Will need to support simultaneous fitting (and sampling).
- Hybrid model candidate

8.6.2.9 Moving Point Source Models

- Fit point source with flux, centroid, parallax, and proper motion parameters.
- May need to support simultaneous fitting.
- Might want to sample this too, at least if we fit it simultaneously with sampled galaxy models.
- Hybrid model candidate

8.6.2.10 Trailed Point Source Models

- Fit PSF convolved with line segment to individual images

8.6.2.11 Dipole Models

- Fit PSF dipole for separation and flux to a combination of difference image and direct image.
- Deblending on direct image very problematic.

Arising primarily due to slight astrometric alignment or PSF matching errors between the two images, or effects such as differential chromatic aberration, flux "dipoles" are a common artifact often observed in image differences. These dipoles will lead to false detections of transients unless correctly identified and eliminated. Importantly, dipoles will also be observed in image differences in which a source as moved less than the width of the PSF. Such

objects must be correctly identified and measured as dipoles in order to obtain accurate fluxes and positions of these objects.

Putative dipoles in image differences are identified as a positive and negative source whose footprints overlap by at least one pixel. These overlapping footprints are merged, and only the sources containing one and only one positive and negative merged footprint are passed to the dipole modeling task. There is a documented degeneracy (`http://dmtn-007.lsst.io`) between dipole separation and flux, such that dipoles with closely-separated lobes of high flux are statistically indistinguishable from ones with low flux and wider separations. We remove this degeneracy by using the *pre-subtracted images* (i.e., the warped, PSF-matched template image and the pre-convolved science image) to constrain the lobe positions (specifically, to constrain the centroid of the positive lobe in the science image and of the negative lobe in the template image). This is done by first fitting and subtracting a second-order 2-D polynomial to the background within a subimage surrounding each lobe footprint in the pre-subtracted images to remove any flux from background galaxies (we assume that this gradient, if it exists, is identical in both pre-subtracted images). Then, a dipole model is fit simultaneously to the background-subtracted pre-subtracted images and the image difference.

The dipole model consists of positive and negative instances of the PSF in the difference image at the dipole's location. The six dipole model parameters (positive and negative lobe centroids and fluxes) are estimated using non-linear weighted least-squares minimization (we currently use the Levenberg-Marquardt minimization algorithm). The resulting reduced χ^2 and signal-to-noise estimates provide a measure by which the source(s) may be classified as a dipole.

We have tested the described dipole measurement algorithm on simulated dipoles with a variety of fluxes, separations, background gradients, and signal-to-noise. Including the pre-subtracted image data clearly improves the accuracy of the measured fluxes and centroids. We have yet to thoroughly assess the dipole measurement algorithm performance on crowded stellar fields. Such crowded fields may confuse the parameter estimates (both centroids and/or fluxes) when using the pre-subtracted images to constrain the fitting procedure, and in such situations, we may have to adjust the prior constraint which they impose.

8.6.2.12 Spuriousness

- Some per-source measure of likelihood the detection is junk (in a difference image).
- May use machine learning on other measurements or pixels.
- May be augmented by spuriouness measures that aren't purely per-source.

8.6.3 Blended Measurement

- Integrate text from blended-measurement doc here.

8.6.3.1 Deblend Template Projection

8.6.3.2 Neighbor Noise Replacement

8.6.3.3 Simultaneous Fitting

8.6.3.4 Hybrid Models In many areas we will need to represent spatial models. This will include models fit to sparse and non-uniformly sampled data. We will support fitting Chebyshev polynomials and splines. We will also support regression techniques like Gaussian Processes.

8.7 Background Estimation

Background estimation will be done on the largest scale feasible first. In the case of Alert Production, this may be on the size of a chip. In DRP, we expect this to be on a full focalplane. An initial low order estimate will be made on a large scale. Each chip will be divided into subregions. For each subregion, the median of the non-masked pixels will be computed. All values for all chips will be fit by an appropriate function (see §8.6.3.4). This will provide a low order background estimation in focal plance coordinates. Note that this can only be done if the instrument signature removal is very high fidelity. Any sharp discontinuity could cause problems with fitting a smooth function.

A higher order background model can be computed per chip. First, the low order background is subtracted from the image. The non-masked pixels will again be binned on a finer grid avoiding bright objects. The median in

each bin is fit by an appropriate function. In practice, this process will likely be iterative.

In the case of Alert Production, there will be no full focalplane model since we expect to process only a single chip in each thread. In this case, we constrain the background with the available un-masked pixels without removing a global background first. Note that image differencing is still possible even in the scenario where there are no unmasked pixels in the science image. The background can be modeled as a part of the PSF matching process. We will want to do background modeling and subtraction in Alert Production when possible because we will want to do calibrated photometry. Even though these measurements are not persisted for science us, they will be very useful for debugging and QA.

If there are so few un-masked pixels in the entire focalplane that even a low order global background is impossible to model, we will not compute a background model. Instead, we will do crowded field photometry only **??**

Crowded fields and composition:
Requirements included working in crowded fields. I think estimating a full focalplane model is the best we can do. If there are no unmasked pixels in the entire FoV, I don't think there is much we can do. I didn't explicitly talk about composition of background models, but this takes that into account by allowing a global model to be subtracted from the single chip image before a higher order model is fit.

8.8 Build Background Reference

AUTHOR: Simon

8.8.1 Patch Level

Background-matching each `CoaddTempExp` (CTE) to a reference exposure performs comparably to fitting the offsets to the N(N-1)/2 difference images, however the co-add quality will depend on the quality of the reference image. Choosing a reference image on a per-patch basis is as simple as choosing the CTE that maximizes both coverage and the SNR of the sky background. Coverage is defined as the fraction of non-NaN pixels in the CTE. NaN pixels arise in CTEs because of gaps between the chips and edges of the visit focal

planes. The camera design specifications indicate a 90% fill factor, and thus approximately 10% of pixels will be NaN due to chip gaps. The SNR of the background can be estimated from either the CTEs themselves, using the variance plane of pixels without the source detection bit mask flagged, or from calibration statistics such as the zero point (a proxy for transparency). In the limiting case that all CTEs have the same coverage, finding the best reference image reduces to the problem of weighting epochs in co-addition. For example, the reference image that minimizes the variance in the co-add is the minimum variance CTE, and the reference image that maximizes SNR in coadd point source measurements is the CTE with the maximum $T_i/\mathrm{FWHM}_i^2\sigma_i^2$[8], where T_i is the transparency, and σ_i^2 the average variance of the pre-scaled exposure. By combining one of these statistics with coverage, we can construct an objective/cost function that relates the importance of coverage and sky-background, and can select a visit that minimizes that quantity objective function.

8.8.2

Constructing reference images for tract-sized co-adds follows the same principle, but requires maximizing the SNR/coverage of a large mosaic constructed from multiple visits. Algorithms for mosaicking partially overlapping images have been well established [e.g. **?** **?**]. By mosaicking visits, applying additive scalar or sloping offsets to calexps, we can generate a tract-sized reference image. Algorithms for selecting visits to construct these fall on a spectrum of computational expense. On the less expensive side is a greedy algorithm which starts with a "best" (as defined above) visit chosen at the center of the tract. Visits can be chosen, scaled, and added one by one in the vicinity, moving outwards. A another option is to choose a small set of visits that completely cover a tract without gaps, which can be cast as a constrained convex optimization problem[9], and mosaic them using standard mosaicking techniques. Finally, the most expensive option would use all the visits to simultaneously tie the visits together using all overlaps while background matching.

- Given multiple overlapping visit images (already warped to a common coordinate system), synthesize a continuous single-epoch image that

[8] to the first order. Don't want to start a fight here

[9] probably

can be used as a reference for background matching.

8.9 PSF Estimation

8.9.1 Single CCD PSF Estimation

Single CCD PSF estimation needs to be run in both Alert Production and in in Data Release Processing. In Alert Production it will be the final PSF model for both direct and difference image measurement. In Data Release Processing, it will be used as an initial bootstrapping step to start off image characterization. We do not intend to include chromatic effects in the PSF at the single CCD estimation phase.

The first step is to select a set of suitable stars to use as PSF exemplars. This can be done by finding clusters in second moment space. In production, we expect that an external catalog with PSF candidates that have been show to be non-varying and isolated will produce better results.

Once a set of candidate stars is selected each star is fit by a set of appropriate basis functions: e.g. shapelets. The PSF is approximated by

$$P = \Sigma_n c_n \Psi_n$$

where Ψ_n is the n^{th} basis function, and c_n is the coefficient for that basis function. We can solve for the coefficients in the least squares sense using a QR decomposition or similar technique. We then have an estimate of the PSF at several locations on the chip. For each of the coefficients we can fit 2D Chebyshev polynomials to each coefficient to model the spatial variation in each component (see 8.6.3.4). By interpolating the fit coefficients, we can derive an estimate of the PSF at any point in the chip.

The order of the spatial model cannot excede number of PSF exemplars in the frame. If there is only a single PSF candidate star, we will assume the PSF is constant across the CCD. In the case of no PSF candidate stars, we will assume a double Gaussian PSF with width set by observation metadata: e.g. FWHM from the guiding system.

Do we need something more complex?:
We can get arbitrarily complex, but I don't thinkn we need a more complex system in the baseline until we show this won't work.

8.10 Wavefront Sensor PSF Estimation

AUTHOR: Jim

- Build an approximate PSF model using only the very brightest stars in the wavefront sensors. Because WF sensors are out-of-focus, these stars may be saturated on science CCDs.
- Model can have very few degrees of freedom (very simple optical model + elliptical Moffat/Double-Gaussian?)
- Only needs to be good enough to bootstrap PSF model well enough to bootstrap processing of science images (but it needs to work in crowded fields, too).
- Being able to go to brighter magnitudes may be important in crowded fields because the shape of the luminosity function may make it easier to find stars with (relatively) significant neighbors.

8.10.1 Full Visit PSF Estimation

AUTHOR: Jim

- Decompose PSF into optical + atmosphere.
- May also use wavefront sensors.
- Constrain model with stars, telemetry, and wavefront data.
- Wavelength-dependent.
- Used in RefineImChar in DRP.
- Must include some approach to dealing with wings of bright stars.

8.11 Model Spatial Variation of PSF

8.11.1 Within a CCD

- Estimate PSF at discrete locations using a set of basis functions
- Fit interpolation functions to fit coefficients to enable interpolation

8.11.2 Over a focal plane – Do we need this?

8.12 Aperture Correction

AUTHOR: Jim

- Measure curves of growth from bright stars (visit-level, at least in DRP)
- Correct various flux measurements to infinite (CCD-level)
- Propagate uncertainty in aperture correction to corrected fluxes; covariance is tricky.

8.13 Astrometric Fitting

AUTHOR: Simon

8.13.1 Single CCD

Used by AP, probably (RHL worries we might need full-visit)

AP will need to do reasonably good astrometeric calibration on single frames in order to do the relative warping between the template and science images. We will use the internal reference catalog used in DRP as the reference catalog. This will be based on astrometry from an external source and will be extended using high quality measurements on coadds from DRP.

We will use a matching algorithm like that outlined in [**?**]. Once we match, a 2D polynomial solution will be fit to minimize the residual.

Dependency:
This introduces a dependency on DRP's internal reference catalog not capture elsewhere.

8.13.2 Single Visit

Full visit astrometric fitting will be done as a bootstrapping step toward higher quality calibration in DRP. All measurements in the visit will be projected to a tangent plane, taking into account all knowledge of the sensor arrangement and optics. The reference catalog (likely the DRP reference catalog) will be projected to the same tangent plane.

Sources will be matched, again using a [**?**] like algorithm. Once the reference and observations are matched, a multi-component WCS will be fit. We expect the components will be related to residuals on the optical model and will included a component to account for the Von Karman turbulence.

8.13.3 Joint Multi-Visit

In the case where there are multiple visits overlapping the same part of the sky, e.g. a patch, we can leverage multiple realizations to beat down the random contribution of the atmosphere to get a better estimate of the optical model and the atmospheric contribution per visit.

The catalogs are stacked and matched using a multi-matching algorithm like OPTICS. At this point, the measurements can be matched to an external catalog for the purposes of absolute astrometry. With all measurementss in hand, a multi-component WCS is fit to all measurements at the same time on order to minimize the residual from the mean position for each object.

8.14 Photometric Fitting

8.14.1 Single CCD (for AP)

- Match to photometric calibration reference catalog
- Calculate single zeropoint using available color terms

8.14.2 Single Visit

- Fit zeropoint (and some small spatial variation?) to all CCDs simultaneously after matching to reference catalog.
- Need for chromatic dependence unclear; probably driven by AP.
- Might be possible to use a "nightly zeropoint" if calibration fields are taken (e.g., during twilight)

8.14.3 Joint Multi-Visit

For DRP, all the observations can be combined in the so-called ubercal procedure to generate the best possible measurement of the relative flux of each source.

- Derive SEDs for calibration stars from colors and reference catalog classifications.
- Utilize additional information from wavelength dependent photometric calibration built by calibration products production to convert observed flux to a flux through a standard atmosphere.
- Fit zeropoint and possibly perturbations to all CCDs on multiple visits simultaneously after matching to reference catalog.

Because the number of stars gets ridiculously large, it can be useful to solve different overlapping regions of the sky in parallel. Once all the regions converge, you can run the same ubercal matrix solution to tie the patches together. The fist step is to solve:

$$m_{ij} = m_i + z_j \tag{2}$$

where m_{ij} is an observed magnitude of star with true magnitude m_i on observation j. While it is possible to include more terms (say, fit out flat-fielding errors at the same time), more terms makes it much harder to solve in parallel. Additional terms also make it easy to make the problem degenerate and it can slow the ubercal algorithm down rapidly. Naively, solving Equation 2 would involve simply computing the psudo-inverse of the sparse m_{ij} matrix. Unfortunately, the inverse of a large sparse matrix is a large dense matrix. Thus one must use iterative solvers such as the LSQR algorithm (a conjugate gradient-type solver) to find the best-fitting values of m_i and z_j.

This method leaves a "floating zeropoint" in the solution (if you add X to all the m_i's, and -X to all the z_j's the solution is the same). If one solves regions of the sky independently, then the floating zeropoints of each region (say a HEALpixel) need to be matched:

$$p_{ij} = p_i + HP_j \tag{3}$$

One open issue is that it's not clear what uncertainties to put in for the different p_{ij}'s (unlike the observed magnitudes where it's relatively easy to calculate a reasonable uncertainty). One must also come up with a method for computing the uncertainties on the returned best-fit parameters.

After solving for all the magnitudes, and merging all the patch zeropoints, there's still the final floating zeropoint (in each filter) that needs to be removed.

One possibility is to use spectrophotometric White Dwarf standards to set the overall photometric zeropoint since they have spectra that should be theoretically calculated to millimag precision. There's also speculation that GAIA BP/RP spectra could provide a good way to do the flux calibration.

8.15 Retrieve Diffim Template for a Visit

In difference imaging a major contributor to the quality of the difference image is the choice of template. We expect that the DRP template generation algorithm will be quite complex. It will potentially involve synthesizing multiple monochromatic templates that will be used to model the effects of DCR.

Ideally, the retrieval will be to select the correct bounding box from the correct master template for the current observation. If not, we expect the template generation algorithm will provide an algorithm to interpret the templates.

8.16 PSF Matching

The essence of image subtraction is to astrometrically register the science image $S(x, y)$ and template image $T(x, y)$, and then match their point spread functions (PSFs) of so that they may be subtracted pixel by pixel. The PSFs are the time–averaged transfer functions of a point source through the Earth's atmosphere, telescope optics, and into the silicon of the detector before being read out. We assume that the science image can be modeled as a convolution of the template image by a PSF–matching kernel $\kappa(u, v; x, y)$, i.e., $S = \kappa \otimes T$. (Indices u, v indicate that the kernel itself is a 2–dimensional function, which varies as a function of position x, y in the image; during convolution and correlation there is an implicit summation over u, v.) Then the difference image, upon which new or variable sources are detected, is given by $D = S - (\kappa \otimes T)$.

8.16.1 Image Subtraction

- Match template image to science image, as in Alert Production and DRP Difference Image processing.
- Includes identifying sources to use to determine matching kernel, fitting the kernel, and convolving by it.

The current implementation of the PSF matching algorithm is summarized in detail by Becker, et al. (2013) (`http://ls.st/x9f`). We model the PSF–matching kernel by decomposing it into a set of basis functions $\kappa(u,v) = \sum_i a_i \kappa_i(u,v)$ [29], where the coefficients are determined via ordinary least-squares estimation:

$$\begin{aligned} C_i &\equiv (\kappa_i \otimes T); \\ b_i &= \sum_{x,y} \frac{C_i(x,y) S(x,y)}{\sigma^2(x,y)}; \\ M_{ij} &= \sum_{x,y} \frac{C_i(x,y) C_j(x,y)}{\sigma^2(x,y)}; \\ a_i &= M_{ij}^{-1} b_j. \end{aligned} \tag{4}$$

$\sigma^2(x,y)$ is the per–pixel variance stored in the `variance` plane of each LSST `exposure`. To generate a spatially varying model for the kernel, we further decompose the relative weights of the basis coefficients a_i into spatially-varying low-order polynomials, i.e. $\kappa(u,v;x,y) = \sum_i a_i(x,y)\kappa_i(u,v)$. We also allow for a spatially-varying differential background between the two images $b(x,y)$ that may be fit for using a low–order polynomial [29, 30]. The image difference is then $D(x,y) = S(x,y) - T(x,y) \otimes \kappa(u,v;x,y) - b(x,y)$.

The basis functions $\kappa_i(u,v)$ are a degree of freedom in this problem. Following [29], we use a set of nGauss = 3 Gaussians, each with a different width σ_i, and each modified by a Laguerre polynomial to a given order (see below). Following more recent studies studies [e.g. 31], we parameterize these different Gaussian widths via a single ratio β, such that $\sigma_{i+1} = \beta \times \sigma_i$ with $\beta = 2.0$. (We note that all constants are defined by `Config` variables and may be adjusted on a per-use basis). We set the overall scale for the σ by noting that, under the assumption that the PSFs of the images are Gaussian (σ_S for the science image and σ_T for the template image), the σ_κ of the matching kernel should be simply $\sigma_\kappa^2 = \sigma_S^2 - \sigma_T^2$. We use this canonical width for the central Gaussian in the basis sequences (i.e., $\sigma_{i=2} \equiv \sigma_\kappa$ when using three Gaussians bases). Each of the three default kernel basis functions are modified by Laguerre polynomials up to order degGauss = $[4, 2, 2]$, respectively. This results in a total number of (non-spatially varying) bases of $\sum_i^{\mathrm{nGauss}} (\mathrm{degGauss}_i + 1) \times (\mathrm{degGauss}_i + 2)/2$, or 27 given the aforementioned defaults.

A spatially-invariant matching kernel $\kappa(u, v)$ is determined separately for image substamps centered on multiple kernel candidates across the image. The kernel candidates are selected using the `DiaCatalogSourceSelector` to query the appropriate reference catalog for appropriate sources to use for PSF matching. This selector allows the user to specify the brightness and color range of the objects, toggle star or galaxy selection, and to include variable objects or not. Sources are vetted for signal-to-noise and masked pixels (in both the template and science image). The matching (spatially-invariant) kernel models $\kappa_j(u, v)$, determined for each kernel candidate j as described above, are examined and filtered by various quality measures. The resulting ensemble of filtered kernel models is used to constrain the spatially-varying kernel model $\kappa(u, v; x, y)$ by fitting the spatially-varying basis kernel coefficients $a_i(x, y)$ with a N^{th}-order 2-dimensional Chebyshev polynomial. This results in the final full spatial solution $\kappa(u, v; x, y) = \sum_i a_i(x, y)\kappa_i(u, v)$, which may be evaluated at each location (x, y) in the image for convolution.

Detection on the difference image occurs through correlation of $D(x, y)$ with the science image's PSF, yielding optimally filtered detection image $D'(x, y) = D(x, y) \circ PSF_S(u, v; x, y)$ where $\circ$ denotes correlation (currently the DM stack uses convolution instead of correlation). The values of the pixels in $D'(x, y)$ provide a maximum likelihood estimate of there being a point source at that position. Detection occurs by simply finding pixels that are more than $N \times \sigma$ above the square root of the per–pixel variance. Alternatively, the science image may be *pre-convolved* with a kernel similar to its PSF, in which case the resulting difference image $D(x, y)$ is already filtered for detection. This latter option has the additional advantage that it help us avoid requiring em deconvolution of the template image, in cases when the template has a wider PSF than the science image.

8.16.2 PSF Homogenization for Coaddition

- Match science image to predetermined analytic PSF, as in PSF-matched coaddition.

In PSF-matched coaddition, input images are convolved by a kernel that matches their PSF to a predefined constant PSF before they are combined. This so-called "model PSF matching" uses the PSF-matching algorithm described in the previous section to match the PSF *model* from an exposure to a pre-determined template (e.g., a constant-across-the-sky double Gaussian)

PSF model. For this task, we realize each PSF model into an exposure-sized grid, and then utilize those as kernel candidates as input for the PSF matching algorithm described above.

8.17 Image Warping

AUTHOR: Jim

8.17.1 Oversampled Images

Oversampled images are warped to a new WCS and resampled using a two dimensional Lancsoz kernel of configurable order. The baselined default order is 3.

The one dimensional Lancsoz kernel of order a is defined as

$$L(x) = \begin{cases} \text{sinc}(x)\ \text{sinc}(x/a) & \text{if } -a < x < a \\ 0 & \text{otherwise.} \end{cases}$$

The two dimensional Lancsoz kernel is $L(x, y) = L(x) \cdot L(y)$.

For each integer pixel position in the remapped image, the associated pixel position in the source image is determined using the source and destination WCS. The warping kernel is then applied to the source image to compute the remapped pixel value. A flux conservation factor is applied based on the relative sizes of the pixel in the source and destination WCS.

For performance reasons, it is desirable to reduce the total number of WCS calculations. It is therefore acceptable to perform the mapping between source and destination images over a regular grid and linearly interpolate between grid points, rather than mapping every pixel independently.

Since chromaticity is accounted for in the PSF rather than the WCS, no special account is taken of color when warping.

> **Note:**
> The above describes the current warping implementation in afw. We should identify deficiencies with the current implementation to establish resource requirements.

8.17.2 Undersampled Images

- Can use PSF model as interpolant if we also want to convolve with PSF (as in likelihood coadds). Otherwise impossible?

8.17.3 Irregularly-Sampled Images

- Approximate procedure for fixing small-scale distortions in pixel grid.

8.18 Image Coaddition

AUTHOR: Jim

- Must be able to do generalized outlier rejection, using histograms of detection masks produced on difference images.
- Needs to propagate full uncertainty somehow.
- Needs to propagate PSFs.
- Needs to propagate wavelength-dependent photometric calibration.
- May need to propagate larger-scale per-exposure masks to get right PSF model or other coadded quantities.
- Should be capable of combining coadds from different bands and/or epoch ranges ranges as well as combining individual exposures.
- Also needs to support combining snaps

8.19 DCR-Corrected Template Generation

Refraction by the Earth's atmosphere results in a dispersion of an astronomical image along the "parallactic angle". This amplitude of this dispersion depends on the spectral energy distribution (SED) of the source and the refractive index of the atmosphere. Differential chromatic refraction (DCR) refers to the SED dependent refraction within a given photometric passband. For the airmass range of the LSST and its filter complement the amplitude of the DCR could be up to 1.1 arcsec in the u band and 0.8 arcsec in the g band. Image subtraction templates that do not account for DCR will result in dipoles in the subtracted images.

The baseline approach for minimizing DCR induced dipoles in image differences is to selected coadded templates that are close in airmass **??**sec:templateSelect]. This will identify three airmass bins (XXX where is this defined) from which PSF matched coadds will be generated (ref).

Given the sensitivity of the number of false positives to the astrometric accuracy of the registration of images and the dependence of this astrometric accuracy on DCR we plan to define an interpolation scheme for generating DCR corrected templates.

8.19.1 Refraction from the atmosphere

Refraction is dependent on the local index of refraction of air $n_0(\lambda)$ at the observatory:

$$n_0(\lambda) = 1 + \left(\left[2371.34 + \frac{683939.7}{130 - \sigma(\lambda)} + \frac{4547.3}{38.9 - \sigma(\lambda)^2} \right] D_s + \left(6487.31 + 58.058\sigma(\lambda)^2 - 0.71150\sigma(\lambda)^4 \right. \right. \tag{5}$$

where

$$\sigma(\lambda) = 10^4/\lambda \quad \left(\mu m^{-1}\right)$$

$$D_s = \left[1 + (P_s - P_w) \left(57.90 \times 10^{-8} - \frac{9.3250 \times 10^{-4}}{T} + \frac{0.25844}{T^2} \right) \right] \frac{(P_s - P_w)}{T}$$

$$D_w = \left[1 + P_w \left(1 + 3.7 \times 10^{-4} P_w \right) \left(-2.37321 \times 10^{-3} + \frac{2.23366}{T} - \frac{710.792}{T^2} + \frac{7.75141 \times 10^4}{T^3} \right) \right] \frac{P}{T}$$

$$P_w = RH \times 10^{-4} \times e^{(77.3450 + 0.0057T - 7235.0/T)} / T^{8.2}$$

where the parameters D_s and D_w are the density factors for dry air and water vapor, respectively, taken from [**?**].

The ratio of local gravity at the observing site to $g = 9.81 m/s^2$ is given by

$$\kappa = g_0/g = 1 + 5.302 \times 10^{-3} \sin^2\phi - 5.83 \times 10^{-6} \sin^2(2\phi) - 3.15 \times 10^{-7} h \tag{6}$$

and, assuming an exponential density profile for the atmosphere, then the ratio β of the scale height of the atmosphere to radius of the observing site from the Earth's core can be approximated by

$$\beta = 4.5908 \times 10^{-6} T \tag{7}$$

where m is the average mass of molecules in the atmosphere, $R_\oplus$ is the radius of the Earth, k_B is the Boltzmann constant, and g_0 is the acceleration due to gravity at the Earth's surface.

Refraction, as a function of wavelength is then given by,

$$R(\lambda) = r_0 n_0(\lambda) \sin z_0 \int_1^{n_0(\lambda)} \frac{dn}{n\left(r^2 n^2 - r_0^2 n_0(\lambda)^2 \sin^2 z_0\right)^{1/2}}$$
$$\simeq \kappa(n_0(\lambda) - 1)(1 - \beta) \tan z_0 - \kappa(1 - n_0(\lambda)) \left(\beta - \frac{n_0(\lambda) - 1}{2}\right) \tan^3 z_0 \tag{8}$$

Parameter	valid range	description	units
P_s	0 mbar$< P_s <$ 4000 mbar	Atmospheric pressure	millibar
RH	$0\% < RH < 100\%$	Relative humidity	Percent
λ	2302Å$< \lambda <$ 20,586Å	Wavelength	Angstroms
T	$250K < T < 320K$	Temperature	Kelvin
ϕ	$0^\circ \leq \phi < 360^\circ$	Latitude of the observing site	Degrees
h	$0\,m \leq h$	Elevation of the observing site	meters
z_0	$0^\circ \leq z_0 < 75^\circ$	Zenith angle	Degrees

Table 2: Definition of parameters and their units

8.19.2 Generating a DCR corrected template

Given a set of observed images, $O(x, z)$, at an airmass of z, and assuming that we know the wavelength dependence of the refraction, we can model the corresponding image at the zenith (or any other airmass), $I(x, 0)$. For simplicity, we will consider only a single row of a sensor as comprising an image, that the direction of the DCR is aligned along, and we will assume the PSF is constant between images.

The impact of DCR is to move flux between pixels as a function of airmass and wavelength. This shift, $R(\lambda, z)$ can be treated as a a shift operator or a convolution, $D(\lambda, z)$ and is known given the refractive index of the atmosphere. If we consider that the zenith image can be decomposed into a linear sum over wavelength, i.e.,

$$I(x', 0) = \sum_\lambda I(x', 0, \lambda) \tag{9}$$

then the observed set of images are given by,

$$O(x, z) = \sum_{\lambda} I(x', \lambda) \otimes D(\lambda, z) \tag{10}$$

Solving for $I(x, \lambda)$ is then a regression problem that can be solve for by minimizing

$$\chi^2 = \sum_{x} O(x) - \sum_{\lambda} I(x', \lambda) \otimes D(\lambda) \tag{11}$$

There are a number of possible approaches for finding the "zenith" image. The convolution can be written as a transfer matrix, T, where the elements of the matrix correspond to the pixel values of $I(x', \lambda)$ that map to the pixel values of $O(x, z)$ given the refraction. Under this mapping, we can write the linear equations as $TI = O$ and by inverting the matrix solve for I. While, T, is clearly sparse the number of terms that must be solved for given the number of wavelengths λ that I is decomposed into means that we require a heavily regularized regression.

The initial implementation for the DCR corrected template will invert the linear equations assuming smoothness in the between adjacent pixels and as a function of wavelength by adopting first and second order finite difference matrices (ref nate).

2 separate regularizations smooth in pixel and smooth in wavelength

matrix extends in size.

An prototype implementation has been demonstrated for the 1D case. A second approach will be to forward model the problem by iteratively updating I based on the set of observations (ref, budavari).

For each approach the number of wavelength bins that $I(x)$ can be decomposed into will depend on the number of observations at different airmass. The assumption of a constant PSF will clearly not hold for the LSST observations but can be incorporated within the convolution Equation 10 or addressed through a separable, wavelength dependent, PSF convolution. The robustness of these techniques will need to be evaluated for low signal-to-noise sources and in the presence of scattered light and artifacts.

8.20 Image Decorrelation

8.20.1 Difference Image Decorrelation

In situations where the signal-to-noise in the template image is not insignificant (e.g., when the template is constructed by co-addition of a small number of

exposures), the resulting image difference will contain autocorrelated noise arising from the convolution of the template with the PSF matching kernel prior to subtraction. This will result in innaccurate estimates of thresholds for `diaSource` detection if the (potentially spatially-varying) covariances in the image difference are not properly accounted for.

A viable alternative in the case of noisy template images is to construct a difference image with a flat noise spectrum, like the original input images [32, 33]. This simply involves multiplying the image difference by a term which removes its frequency dependence,

$$D(k) = [S(k) - \kappa(k)T(k)] \sqrt{\frac{\sigma_S^2 + \sigma_T^2}{\sigma_S^2 + \kappa^2(k)\sigma_T^2}}, \tag{12}$$

where S is the science image, T is the template, σ_S^2 and σ_T^2 are their respective variances, and κ is the PSF-matching kernel which, when convolved with the template, matches the PSF of the template to that of the science image. κ may be solved for (in real space) as described in Section 8.16. Then the multiplication by the square-root term in Equation 12 may be interpreted as applying a post-image-differencing convolution kernel which "removes" the pixel-wise correlation which was added by convolution of the template by the PSF-matching kernel. The PSF of the resulting decorrelated difference image ϕ_D then equals the PSF of the science image ϕ_S, convolved with the post-differencing kernel:

$$\phi_D(k) = \phi_S(k) \sqrt{\frac{\sigma_S^2 + \sigma_T^2}{\sigma_S^2 + \kappa^2(k)\sigma_T^2}}. \tag{13}$$

We are investigating this approach and have shown that, for idealized situations, the resulting image differences are statistically indistinguishable from those generated using the "Proper image subtraction" technique proposed by [33].

Issues arising from complications often seen in real-world data such as spatially-varying PSFs and/or poorly-evaluated matching kernels, spatially variable backgrounds and/or noise, and possibly non-Gaussian or heteroschedastic noise need to be further evaluated. Such tests are currently underway on simulated and real data. These tests could highlight the advantages of the method proposed here over the proposal of [33], including: no requirement for accurate measurement of the PSFs of the science or template

images, and thus the ability to to account for errors in astrometric alignment and to directly model spatially varying differential PSFs.

8.20.2 Coadd Decorrelation

AUTHOR: Jim

- Fourier-space/iterative deconvolution of likelihood coadds, as in DMTN-15.
- Need to test with small-scale research before committing to this approach.

8.21 Star/Galaxy Classification

AUTHOR: Jim

8.21.1 Single Frame S/G

- Extendedness or trace radius difference that classifies sources based on single frame measurements that can utilize the PSF model. Used to select single-frame calibration stars, and probably aperture correction stars.

8.21.2 Multi-Source S/G

- Aggregate of single-visit S/G post-PSF numbers in jointcal.

8.21.3 Object Classification

- Best classification derived from multifit and possibly variability.

8.22 Variability Characterization

Following the DPDD, lightcurve variability is characterized by providing a series of numeric summary 'features' derived from the lightcurve. The DPDD baselines an approach based on Richards et al. [24], with the caveat that ongoing work in time domain astronomy may change the definition, but not the number or type, of features being provided.

Richards et al. define two classes of features: those designed to characterize variability which is periodic, and those for which the period, if any, is not important. We address both below.

All of these metrics are calculated for both Objects (DPDD table 4, `lcPeriodic` and `lcNonPeriodic`) and DIAObjects (DPDD table 2, `lcPeriodic` and `lcNonPeriodic`). They are calculated and recorded separately in each band. Calculations for Objects are performed based on forced point source model fits (DPDD table 5, `psFlux`). Calculations for DIAObjects are performed based on point source model fits to DIASources (DPDD table 1, `psFlux`). In each case, calculation requires the fluxes and errors for all of the sources in the lightcurve to be available in memory simultaneously.

8.22.1 Characterization of periodic variability

- Characterize lightcurve as the sum of a linear term plus sinusoids at three fundamental frequencies plus four harmonics:

$$y(t) = ct + \sum_{i=1}^{3}\sum_{j=1}^{4} y_i(t|jf_i) \tag{14}$$

$$y_i(t|jf_i) = a_{i,j}\sin(2\pi jf_i t) + b_{i,j}\cos(2\pi jf_i t) + b_{i,j,0} \tag{15}$$

  where i sums over fundamentals and j over harmonics.

- Use iterative application of the generalized Lomb-Scargle periodogram, as described in [24], to establish the fundamental frequencies, f_1, f_2, f_3:
  - Search a configurable (minimum, maximum, step) linear frequency grid with the periodogram, applying a $\log f/f_N$ penalty for frequencies above $f_N = 0.5\langle 1/\Delta T\rangle$, identifying the frequency f_1 with highest power;
  - Fit and subtract that frequency and its harmonics from the lightcurve;
  - Repeat the periodogram search to identify f_2 and f_3.

- We report a total of 32 floats:
  - The linear coefficient, c (1 float)
  - The values of f_1, f_2, f_3. (3 floats)
  - The amplitude, $\mathrm{A}_{i,j} = \sqrt{a_{i,j}^2 + b_{i,j}^2}$, for each i, j pair. (12 floats)

- The phase, $\mathrm{PH}_{i,j} = \arctan(b_{i,j}, a_{i,j}) - \frac{jf_i}{f_1} \arctan(b_{1,1}, a_{1,1})$, for each i, j pair, setting $\mathrm{PH}_{1,1} = 0$. (12 floats)
- The significance of f_1 vs. the null hypothesis of white noise with no periodic signal. (1 float)
- The ratio of the significance of each of f_2 and f_3 to the significance of f_1. (2 floats)
- The ratio of the variance of the lightcurve before subtraction of the f_1 component to its variance after subtraction. (1 float)

NB the DPDD baselines providing 32 floats, but, since $\mathrm{PH}_{1,1}$ is 0 by construction, in practice only 31 need to be stored.

8.22.2 Characterization of aperiodic variability

In addition to the periodic variability described above, we follow [24] in providing a series of statistics computed from the lightcurve which do not assume peridoicity. They define 20 floating point quantities in four groups which we describe here, again with the caveat that future revisions to the DPDD may require changes to this list.

Basic quantities:

- The maximum value of delta-magnitude over delta-time between successive points in the lightcurve.
- The difference between the maximum and minimum magnitudes.
- The median absolute deviation.
- The fraction of measurements falling within 1/10 amplitudes of the median.
- The "slope trend": the fraction of increasing minus the fraction of decreasing delta-magnitude values between successive pairs of the last 30 points in the lightcurve.

Moment calculations:

- Skewness.

- Small sample kurtosis, i.e.

$$\text{Kurtosis} = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{i=1}^{n} \left(\frac{x_i - \overline{x}}{s} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)} \tag{16}$$

$$s = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (x_i - \overline{x})^2} \tag{17}$$

- Standard deviation.

- The fraction of magnitudes which lie more than one standard deviation from the weighted mean.

- Welch-Stetson variability index J [26], defined as

$$J = \frac{\sum_k \text{sgn}(P_k) \sqrt{|P_k|}}{K},$$

  where the sum runs over all K pairs of observations of the object, where sgn returns the sign of its argument, and where

$$P_k = \delta_i \delta_j \tag{18}$$

$$\delta_i = \sqrt{\frac{n}{n-1}} \frac{\nu_i - \overline{\nu}}{\sigma_\nu}, \tag{19}$$

  where n is the number of observations of the object, and ν_i its flux in observation i. Following the procedure described in Stetson [26], the mean is not the simple weighted algebraic mean, but is rather reweighted to account for outliers.

- Welch-Stetson variability index K [26], defined as

$$K = \frac{1/n \sum_{i=1} N|\delta_i|}{\sqrt{1/n \sum_{i=1} N|\delta_i^2|}},$$

  where N is the total number of observations of the object and δ_i is defined as above.

Percentiles. Taking, for example, $F_{5,95}$ to be the difference between the 95% and 5% flux values, we report:

- All of $F_{40,60}/F_{5,95}$, $F_{32.5,67.5}/F_{5,95}$, $F_{25,75}/F_{5,95}$, $F_{17.5,82.5}/F_{5,95}$, $F_{10,90}/F_{5,95}$
- The largest absolute departure from the median flux, divided by the median.
- The radio of $F_{5,95}$ to the median.

QSO similarity metrics, as defined by Butler & Bloom [10]:

- $\chi^2_{\mathrm{QSO}}/\nu$.
- $\chi^2_{\mathrm{False}}/\nu$.

8.23 Proper Motion and Parallax from DIASources

Every time we observe another apparition of a DIAObject, we have an opportunity to update/improve the proper motion and pararllax models. The DIASources are associated with the current best model from the DIAObject. The proper motion and parallax are then refit using the new observation.

Do we actually want to do this:
I had a conversation about this with Colin. In reqlity we can't do as good a job with proper motion and parallax in nightly processing as we can in DRP. It's true that we would have no estimate of the proper motion or parallax until the first release if we do not calculate it in nightly, but I'd argue that before the first release we don't have the baseline to calculate an accurate anyway. Further, the measurement in DRP can be much better since we can do it as part of joint astrometric fitting. If we don't measure pm and parallax in nightly, we could still use the DRP measurement in the associated DRP object for association.

8.24 Association and Matching

Association between an external catalog of sources with objects detected from an LSST visit is critical to many aspects of the nightly and data release processing. External catalogs may come from photometric or astrometric standards

(e.g. catalogs from GAIA), from previous LSST observations (e.g. Objects), or from catalogs derived from previous observations (e.g. the ephemerides of moving sources).

For cross-matching to reference catalogs the algorithm must be able to account for variation in scale and rotation of the field, and for optical distortions within the system. It must be fast and robust to errors and capable of matching across different photometric passbands.

For association with previous LSST observations the algorithms will need to be probabilistic in nature, must account for cases where the image quality results in the blending of sources, must work at high and low Galactic latitude, and must allow for sources with varying and variable SEDs.

Algorithmic components in this section will typically (but perhaps not always) delegate to the N-Way Matching software primitives, which provide spatial indexing and data structures for simple spatial matches.

8.24.1 Single CCD to Reference Catalog, Semi-Blind

Given a set of sources detected on a single sensor, and a corresponding reference catalog we adopt a simple pattern matching algorithm to cross-match between the catalogs. We assume that the sources detected on the sensor have approximate positions given by the telescope's initial estimate of a WCS, that we know the plate scale of the system, and that positional errors are available for both the sensor and reference catalog.

Cross-matching is undertaken using the Optimistic Pattern Matching (B) algorithm of Tabur [**?**]. The algorithm defines an order m (default 6) size $m-1$ acyclic connected tree (XXX check this definition) as the pattern to match between catalogs. The details of the LSST implementation of the Optimistic Pattern Matching (B) algorithm are as follows:

- An optical distortion model is subtracted from the positions of the detected sources on the sensor to define a gnomonic plane projection.
- Detected sources are ordered in descending brightness and the brightest n stars (default = 50) are selected, I
- Given the extent of the sensor (defined from the initial WCS) the brightest n sources are extracted from the reference catalog, R
- The pairwise distances and position angles between the reference catalog sources, R, are measured (generating $n(n-1)/2$ pairs)

- For the m brightest sources in I the length of the edges and the position angles of the edges of the graph are calculated (with the brightest source the center of the graph). Angles are relative to the sensor orientation and distances are in angular coordinates.

- A binary search identifies all pairs in R with a length matching the length of the edge containing the brightest two sources (within a tolerance that has a default pf 3 arcsec). The difference in position angle between the reference and source edges is assumed to be due to the rotation of the sensor relative to the reference catalog and this position angle difference is accounted for in all remaining matches

- The remaining $m - 2$ edges are compared to the pairs in R and a match is assumed if the edge length and postion angles are within the tolerances (defaults 3 arcsec and 1 degree respectively)

- If $m - 1$ matches are not found the search repeats; initially for the remaining matches to the length of the edge corresponding to the brightest two sources and then for a new graph that excludes the brightest object from$I$ and finds the next brightest m sources

Once $m - 1$ edges match an initial verification step is performed where a gnomonic projection of the reference catalog is fit to the matched stars. Given a consistent fit to the gnomonic projection all sources, I, and reference objects, R are then matched in sensor coordinates (sorted by brightness) with the brightest source in I selected when two sources are within the match tolerance (default 3 arcsec XXX check).

For the case of no WCS for the sensor or a significant error in the WCS ($>$ 3 arcsec) a blind matching will be undertaken using the algorithms in astrometry.net (ref)

8.24.2 Single Visit to Reference Catalog, Semi-Blind

For single visit cross-matching matches all sources within a focal plane will be matched to the reference catalog, R. This case is a perturbation on the original Tabur algorithm. It must account for significant distortions, and deviations from a Euclidean space when calculating a gnomonic projection across the LSST field-of-view.

Modifications from the single sensor cross matching are:

- Given a model for the postions and orientations of the sensors on the focal plane sensor coordinates are transformed to focal plane coordinates (XXX what algorithm)
- the focal plane coordinates are corrected for the optical distortion model to provide a Euclidean space
- Work in 3D space?

  Use budavari algorithm?

  Want to match in focal plane coordinates, so also needs to transform reference catalog.
- Run prior to single-visit WCS fitting, with only telescope's best guess as a starting WCS.

focal plane coordinates - from sensor to focal plane and apply optical distortion model

run match in 3D distance space (using the budavari approach?)

8.24.3 Multiple Visits to Reference Catalog

AUTHOR: Jim

- Match sources from multiple visits to a single reference catalog, assuming good WCS solutions.

8.24.4 DIAObject Generation

Assuming that all DIAObject positions been propagated to the MJD of the visit (including proper motion and the generation of ephemerides for SSObjects) association of a DIASource with a DIAObject simplifies to the probabilistic assignment of a DIASource to a DIAObject.

We define this assignment in terms of the Bayes Factor, B, that defines the ratio of the probability that the observed data, D, is more likely given a model, H, that the DIASource and DIAObject are matched, than for a model K, where the sources do not match, K.

$$B(H,K|D) = \frac{p(D|H)}{p(D|K)} \tag{20}$$

see Budavari and Szalay [**?**].

Assuming a normal distribution for positional uncertainties the Bayes Factor is given by,

$$B(H,K|D) = \frac{sinhw}{w}\prod_{i=1}^{n}\frac{w_i}{sinhw_i} \tag{21}$$

with

$$w = |\sum_{i=1}^{n} w_i\bar{x_i}| \tag{22}$$

and x_i the 3D unit vector for a position on a sphere, and $w = 1/\sigma^2$ with σ the uncertainty on the position.

For the case of two sources and small uncertainties on the positions this simplifies to

$$w = \sqrt(w_1^2 + w_2^2 + 2w_1w_2\cos(\phi) \tag{23}$$

and

$$B = \frac{2}{\sigma_1^2 + sigma_2^2}exp(-\frac{\phi^2}{2(\sigma_1^2 + sigma_2^2)} \tag{24}$$

with ϕ the angle between the positions.

For all pairs of sources within a given tolerance the Bayes Factor will be calculated and the source with the largest Bayes Factor assigned to the DIAObject. For sources above the Bayes Factor threshold that were not assigned the Bayes Factor and DIAObject ID will be persisted in the DIASource. Thresholds for the Bayes Factor will be derived from simulations

An extension to the Bayes Factor association to account for unknown proper motions is possible [**?**]

8.24.5 Object Generation

AUTHOR: Jim

- Match coadd detections from different bands/SEDs/epoch-ranges, merging Footprints and associating peaks.
- Also merge in DIASources or (if already self-associated) DIAObjects.

8.24.6 Blended Overlap Resolution

AUTHOR: Jim

- Given two or more overlapping blend families (with associated measurements), merge them by selecting the "best" measurement for each child object.

8.25 Raw Measurement Calibration

AUTHOR: Jim

- Apply astrometric and photometric calibrations to measurements in raw units, transforming them to calibrated quantities.
- May be applied within the database after ingest in some contexts, but needs to be available outside the database as well.

8.26 Ephemeris Calculation

Ephemeris calculation for the purpose of association in the nightly pipelines and for attribution and precovery in dayMOPS will require an indexing algorithm as well as anumerical integration phase. The JPL Horizons page reports $700,000$ asteroid orbits. This is far too many to run forward for every observation we will take. Thus, we will need to predict which bodies are likely to cross an aperture on the sky.

There are tools that allow for orbit prediction. As a baseline, we suggest using the OOrb (https://github.com/oorb/oorb). Regardless of the tool we use in production, it will need the following features:

- `Propogation`: Take a set of orbits and do the full numerical integration forward/backward in time to produce a new set of orbital elements
- `Prediction`: Produce a set of topocentric positions for a given set of objects at a particular time

In order to make spatial lookup of the orbits of interest fast, we will checkpoint the location of every solar system object at the beginning, middle and end of each upcoming night. The checkpointing will involve saving topocentric positions for all solar system objects and saving the propogated

orbital parameters at the end of the night. We cannot precompute this for the duration of the survey because we will find new objects and we will update orbits of known objects. This computation will be done daily as part of the prep-work for nightly observing. This is not a large computational challenge and is pleasingly parallel.

During nightly processing ephemeris prediction will be carried out on the objects that may intersect the visit in question. For spatial filtering, all objects will be assumed to move linearly over half the night. The on-sky visit aperture with an appropriate buffer to account for the maximum acceleration of a solar system object over $\tilde{4}$ hours will determine which objects potentially fall in the exposure. For those few thousand objects, precise ephimerides will be calculated for the purpose of association.

8.27 Make Tracklets

Tracklets are the building blocks of orbits. The process of linking observations is to pair up all observations that are within some distance of each other given a maximum on sky velocity. For any source, tracklets can be found by looking in circular apertures in subsequent visits with the radius of the circular aperture growing with time by $v_{max}dt$ for v_{max} in appropriate units. In practice we will follow [**?**] and build KD-trees on detections from each visit. KD-trees allow fast range searches. Linking up tracklets simply involves a series of range searches on available visits.

The number of tracklets goes up as $O(n^2)$ where n is the number of images covering a region in a given time span. However, many of the tracklets are degenerate. I.e. for an object moving slowly across the sky, it's possible that the beginning, ending and every other image inbetween could be within the velocity cut. These degenerate tracks are "collapsed" by computing a velocity vector for each tracklet. The tracklets are then binned in speed, perpendicular distance from a reference location, and direction. Similar to a Hough transform, degenerate tracklets will tend to accupy similar bins. Bins with multiple tracklets will be used to reduce the tracklets to the longest linear tracklet consistent with the tracklets.

When tracklets are collapsed, we gain more information about the collasped tracklet since we have multiple observations of it. This allows some tracklets to be dismissed ds spurious linkages. Any observation that deviates from the linear fit to the collapsed tracklet by a threshold amount will be discarded as spurious.

8.28 Attribution and precovery

Precovery is the process of adding 'orphan' DIASources, those that do not belong to a SSObject or DIAObject, to a SSObject. Any time an SSObjects orbital parameters change significanly, it's possible that DIASources not associated previously could now match. The process is to calculate ephemerides backward in time from the earliest observation as far as is possible given the uncertainty in the orbit. These ephemerides are compared to the orphan DIASources. If a match is found, a new orbit is fit and if the new orbit is a better fit than the old one, the SSObject is updated with the new fit.

Attribution is the process of adding tracklets to known SSObjects. For a given time window, topocentric ephemerides are calculated for all SSobjects that could potentially intersect any of the images in that window at the observation times of each of the images. These ephimerides are then compared to the tracklets in the time window. If any of them match in locatio and velocity, a new orbit is calculated. If the new orbit is better than the old on, the tracklet is tagged as being part of that SSObject and the SSOBject is updated with the new orbital parameters.

Since both attribution and precovery involve updating the SSObject, this process is recursive. The cadence of the recursion will be daily. Since we run attribution and precovery at least once during every run of the moving object pipeline, there is little need to recurse on shorter timescales.

8.29 Orbit Fitting

Given a database of tracklets not associated with any SSobject, we will look for tracks that match physical orbits.

Finding tracks is a tricky problem. We will follow the approach presented in [**?**]. Where all except the most quickly moving bodies will have linear motion over a night, this is not true over the LSST discovery window of 30 days. In order to have high quality candidate tracks, we require three tracklets per track. Scince there are limits to how fast solar system objects can move and also how fast the can accellerate, we can build a KD-tree on the tracklest in a given observationin velocity and position. Given a node, this implies an acceleration for nodes in other trees. Since we require at least one support tracklet between any two endpoint tracklets, we can discard any nodes that do not have at least on matching node between them. With this in mind, we search for pairs of tracklets that match the velocity and acceleration

cuts and are on different nights. If there is also at least one node between them in time (and on a different night than either of the endpoints) that also pass the velocity and acceleration criteria, all nodes are searched for tracks.

In order to validate candidate tracks, a quadratic fit to the orbit is attempted with higher order topocentric effects due to reflex motion of the Earth included. These effects depend on the distance of the object from the Earth, so the range is fit for as part of the fitting process. For tracks with sufficiently good χ^2, the tracks are passed on to an orbit fitter. As above, there are tools to fit for orbital parameters given a set of observations. We will use these as our final orbit determination.

Finally, all orbits will be compared. If there are any orbits that are sufficiently close in parameter space, they will be merged into a single orbit and the SSObject database updated.

9 Software Primitives

9.1 Cartesian Geometry

- Geometry in image, focal plane coordinate systems.
- Includes continuous (floating point) and discrete (integer) versions of some things; integer versions refer to entire pixels, which makes them somewhat different.
- May need augmented versions of some classes to allow them to know what coordinate system they're in.
- May need augmented versions of some classes to store uncertainty.
- All classes need to be persistable. Some need to be persistable to individual records (via e.g. FunctorKeys)
- All classes have counterpart Spherical classes related to them by WCS transforms.

9.2 Points

- Needs sensible handling of arithmetic operators. Currently implemented by making Extent a separate class, adding CoordinateExpr for element-wise comparisons – but those aren't the only options.
- Need continuous (PointD) and discrete (PointI) versions.
- 3-d continuous Point/Extent also useful, especially in representing unit vectors on the sphere. May not need to be the same template class (and maybe it shouldn't be, if it simplifies our code).
- Probably need to make these immutable (or have an immutable version) at least in Python so they can be exposed as properties.
- Needs to be persistable to individual records in the table library.
- Probably needs augmented version with uncertainty.
- Probably needs augmented version with coordinate system.

9.3 Arrays of Points

- Need containers for Points that work well in both C++ and Python – more than just a naively-wrapped `std::vector` would provide (in terms of NumPy interoperability, mostly). Probably something based on ndarray, translating to a NumPy array with x and y fields?
- Unclear if we need a container with dynamic size. Could probably use `std::vector` and Python `list` while building arrays, then freeze into a fixed, viewable array.
- Probably needs augmented version with coordinate system (all points in same coordinate system).
- Should look into what Astropy does here.

9.4 Boxes

- Need continuous (BoxD) and discrete (BoxI) versions, with different relationships between min, max, and dimensions.
- Probably need to make these immutable (or have an immutable version) at least in Python so they can be exposed as properties.
- Needs to be persistable to individual records in the table library.
- Spherical counterpart is actually Spherical Polygon.

9.5 Polygons

- Only continuous version needed.
- Mostly used to represent large-scale masks (regions around bright stars, vignetted regions).
- Needs to support rasterization to mask and/or footprint.
- Needs to support efficient topological operation and predicates with other Polygons, Points, and Boxes (probably not Ellipses).

9.6 Ellipses

- Only continuous version needed.
- Mostly used to represent source/object shapes.
- Needs to support many different ellipse parameterizations.
- Needs to support fast evaluation of elliptically-symmetric functions (via computing the generating affine transform)
- Need version that knows its position and one that doesn't.
- Needs to support rasterization to mask and/or footprint
- May need an immutable version in Python (not yet certain).
- May needan augmented version with uncertainty.

9.7 Spherical Geometry

The spherical geometry library is a dependency of the database as well as applications, it includes fundamental types that are logically present in database tables (as groups of fields), and some geometry classes are important for spatial indexing.

- Geometry on the sky
- All positions and distances are Angles; need type safety for angle unit.
- May need augmented versions of some classes to allow them to know what coordinate system they're in.
- May need augmented versions of some classes to store uncertainty.
- All classes need to be persistable. Some need to be persistable to individual records (via e.g. FunctorKeys)

9.8 Points

- Needs sensible handling of arithmetic operators. Point/Extent split probably an even better idea here.
- Probably need to make these immutable (or have an immutable version) at least in Python so they can be exposed as properties.
- Needs to be persistable to individual records in the table library.
- Probably needs augmented version with uncertainty.
- Probably needs augmented version with coordinate system.

9.9 Arrays of Points

Same requirements as Cartesian Arrays of Points.

9.10 Boxes

- Not obvious we need this at all.
- Defined on long/lat grid, so not a box in any Cartesian projection.
- Needs special handling for poles?

9.11 Polygons

- Connecting points with great circles is probably sufficient, even if this only approximately maps to Cartesian polygons in most projections; we will have very few Cartesian polygons that extend beyond the size of one CCD, and for those great circles should be fine.
- Needs to support efficient topological operation and predicates with other Polygons, Points, and Boxes (probably not Ellipses).
- May need to support rasterization to some spherical pixelization scheme (e.g. HTM), but those requirements are probably driven more by database.

9.12 Ellipses

- Doesn't need to be a true spherical geometry - we really just need a Cartesian ellipse with angular position and size, defined via a gnomonic plane projection centered on the ellipse. All spherical ellipses will be small enough that we don't have to worry about the topology of large ellipses.
- Probably needs augmented version with uncertainty.

9.13 Images

9.13.1 Simple Images

- Conceptually just a numpy array + xy0
- Still need to fix xy0 behavior on iterators/locators
- Constness is a mess
- Need more Pythonic interface to templates.
- Needs FITS import/export in addition to some round-trip internal representation. May need FITS roundtrip.

9.13.2 Masks

- Should not rely entirely on bits in integer images; consider extending to include:
  - a container of Footprints (actually PixelRegions).
  - a container of Polygons or other geometries.
- May want to switch from compile-time number of bits (Array¡uintN,2¿) to dynamic (Array¡uint8,3¿).
- Can we do anything to fix confusing semi-singleton mask plane dict behavior, while getting the functionality we want?
- Also all requirements of simple images.

9.13.3 MaskedImages

Includes components:

Image A 2-d array of calibrated, background-subtracted pixel values in counts.

Mask A boolean representation of artifacts, detections, saturation, and other image. This may include (but is not limited to) a 2-d integer arrays with bits interpreted as different "mask planes"; it may also include using Footprints to describe labeled regions.

Variance A representation of the uncertainty in the image. This includes at least a 2-d array capturing the variance in each pixel, and it may involve some other scheme to capture the variance.

Other notes:

- Want to support constant mask and variance, probably via single-pixel images with zero strides.
- Want NumPy-like view of all three planes. Probably a new object that implements array interface without inheriting from numpy.ndarray.
- Also all requirements of simple images.

9.13.4 Exposure

Includes components:

MaskedImage Image, mask, variance.

Background An object describing the background model that was subtracted from the image; the original unsubtracted image can be obtained by adding an image of this model to the Exposure's image plane. Backgrounds are more complex than merely an image or even an interpolated binned image; background estimation will proceed in several stages, and these stages (which may happen in different coordinate systems) must be combined to form the full background model.

PSF A model of the PSF; see PSF. This includes a model for aperture corrections.

WCS The astrometric solution that related the image's pixel coordinate system to coordinates on the sky; see WCS.

PhotoCalib The photometric solution that relates the image's pixel values to magnitudes as a function of source wavelength or SED. Some PhotoCalibs may represent global calibration and some may represent relative calibration.

CameraGeom Object describing the detector this image corresponds to, if applicable. Could go on a subclass of Exposure for sensor-level images.

CoaddInputs Table(s) describing the inputs that went into this coadd. Could go on a subclass of Exposure for sensor-level images.

Other notes:

- Probably missing some components in the above list.
- Want to forward more MaskedImage operations to Exposure (so we don't have to say getMaskedImage() all the time).
- Need to be able to persist and pass around non-image components separately.
- Need to integrate ValidPolygon component in current design with Mask.
- Needs FITS import/export in addition to some round-trip internal representation. May need FITS roundtrip.

9.14 Multi-Type Associative Containers

- Replacement(s) for PropertyList/PropertySet.
- Needs to be more Pythonic; more like dict.
- Need a variant that can be used to round-trip FITS headers.

9.15 Tables

All classes need round-trip internal persistence and FITS, ASCII, SQL import/export.

9.15.1 Source

- In-memory data structure for Source, DIASource, ForcedSource tables.
- Has (Heavy)Footprint attached.
- Always has ID, coord (at least conceptually; may be computed on-the-fly).
- Has slots.

9.15.2 Object

- In-memory data structure for Object, DIAObject.
- Must be able to represent information from multiple bands and coadd flavors (array fields? nested rows of another type?)
- Needs to have multiple (Heavy)Footprints attached.
- Needs to have join to table of Monte Carlo samples.
- Maybe just want to be able to attach arbitrary objects?
- Has slots.

9.15.3 Exposure

- Want to be able to store all non-image Exposure components in a single record.

9.15.4 AmpInfo

- Used to record electronic parameters for amplifiers in Camera Descriptions.

9.15.5 Reference

- Need table class for (external) reference catalogs.
- Has a lot in common with Source and Object, but needs fewer attachments, and typically is in calibrated units instead of raw units.

9.15.6 Joins

- Need an in-memory representation of relationships (one-many, many-many, maybe one-one) between tables.
- Need pointer-like behavior (e.g. for one-many, a Record looks like it has another Catalog as one of it fields)
- Used to represent outputs of N-Way Matching.
- Used to store samples with Object tables.
- Used to related ForcedSource to Object and DIASource to DIAObject.

9.15.7 Queries

- Need basic SQL-WHERE-like query support, at least in Python.
- Could maybe delegate this to Pandas and/or Astropy, use NumPy expressions.
- May need to support string expressions (supplied as configuration parameters, for instance).
- Actually being able to write SQL could be very nice. In-memory sqlite back-end? Some other third-party SQL parser, with our own (numpy-compatible) storage backend?

9.15.8 N-Way Matching

AUTHOR: MWV

- Match sources and associate objects from M catalogs each with ∼N sources. The API should match in either (x, y) or (RA, Dec). Positions for source detections solutions will be assumed to already be correct. Order of individual catalogs should not matter. Algorithm will need to be able to run on M∼1,000 visits. Such a tool will allow flexible analyses without the requirement for a larger database structure or full coadd-based object identifiction and forced photometry. Even within the framework of a complete Level-2 DRP release, such a N-way matching capability will also be important for comparing the results

of single-visit photometry with the deep coadd-based object detection and forced photometry. A specific example use case for lightweight quality assessment is taking the processed catalogs for M=1,000 images each with N=2,000 sources and creating object associations add derived repeatability and time-variable summary statistics. This algorithm and associated API should provide a general purpose tool useful for algorithm developers, data quality assessment, and science users. A trivial in-memory version (using full catalogs), a streamlined in-memory version (load only the coordinates), and a larger-than-memory version will each be useful and important and will entail increasingly more significant design and performance efforts.

9.16 Footprints

All classes need to be persistable (usually as components of larger data structures such as tables or masks).

- Footprint itself includes both Spans and Peaks, representing a detection.
- Footprints are guaranteed to be contiguous.
- Concept is fine, class itself needs a lot of cleanup.

9.16.1 PixelRegions

- Very lightweight data structure that is just a container of Spans - represents just a pixel region.
- Needs large suite of topological operations.
- May be noncontiguous.

9.16.2 Functors

- Run functions on each pixel in a PixelRegion
- Needs to support unary, binary, maybe ternary?
- Needs to support modifing arguments in-place and returning them.
- Abstracts whether pixels are from a 2-d image or a flattened 1-d array.

9.16.3 Peaks

- Needs to record position, rough flux.
- Needs to be extensible to also hold at least flags.
- Needs very low overhead; will have many, many peaks.
- Current implementation uses custom table class, but is a bit clunky.

9.16.4 FootprintSets

- Specialized container for Footprints.
- Because Footprints are guaranteed contiguous, most topological operations are here instead (as they have the potential to merge or split Footprints).
- Needs better interoperability with table library, which is also a kind of container of Footprints.

9.16.5 HeavyFootprints

- A Footprint with its own pixels, stored as a flattened 1-d array.
- May sometimes need mask and variance as well, may not.
- Definitely need a version that doesn't have mask and variance.

9.16.6 Thresholding

- Low-level operations for finding above-threshold regions and peaks within them.
- Should decompose into operations that just find above-threshold regions (as PixelRegions), operations that just find Peaks within PixelRegions, and a higher-level operation to do both, returning a FootprintSet.

9.17 Basic Statistics

- Various robust statistics for central tendency and distribution widths, measured on 2-d and 1-d arrays.
- Needs to be able to make use of mask and variance arrays.
- Needs to work on 2-D Images and MaskedImages
- Needs to work on stacks of aligned pixels for coaddition.

9.18 Chromaticity Utilities

All classes need to be persistable (usually as components of larger data structures such as tables or camera descriptions).

9.18.1 Filters

- One or more classes that represent the complete wavelength-dependent throughput of the system and all of the multiplicative components that comprise it (actual filter curves, sensor QE, etc.).
- Needs to be able to handle position-dependence as well, including coordinate transformations of position dependency (from e.g. filter coordinate system to focal plane to individual sensors).
- Need concrete classes that are mostly fixed with a parameters to represnet highly-variable aspects (e.g. atmospheric absorption)
- Probably need another class to represent a telescope or survey's set of filters.

9.18.2 SEDs

- One or more classes that represent object spectra.
- Needs interoperability with filter classes (integrate to yield fluxes, ...?)
- Defines canonical approach to inferring SED from colors (which requires a library of canonical SEDs)
- Used to evaluate PSF and PhotoCalibs.

9.18.3 Color Terms

- First-order approximations to mapping between different filter systems.
- Unclear (to jbosch) whether we'll use these at all in LSST production pipelines, but definitely needed for work with precursor data.

9.19 PhotoCalib

Needs to be persistable (usually as components of larger data structures such as Exposure).

- Spatially- and wavelength-dependent photometric calibration.
- May be relative or absolute.
- Needs to represent rescalings somehow (change from flats-for-backgrounds to monochromatic object flats).
- Needs to hold its own uncertainty (may not be just one number).
- May ultimately be a hierarchy of classes, intead of just one.

9.20 Convolution Kernels

Probably needs to be persistable, but only to ease persistence of higher-level objects that may be built on top of them.

- Supports spatially-varying convolution with a variety of tricks for special kernels (e.g. spatially varying linear combinations of fixed kernels, kernels separable in x and y).
- Must support correlation as well.
- Closely related to PSFs, but kernels are not wavelength-dependent, and PSFs are. Not clear whether difference imaging kernels should actually be Kernels (they could be more like PSFs if they're wavelenght-dependent).
- Closely related to image resampling. Can a resampling kernel be a Kernel? Implies that output pixel grid could be different from input pixel grid.

- May want to be able to compose Kernels.
- Needs to support approximation on different spatial scales (smoothly varying kernels need not be fully evaluated at every pixel).

9.21 Coordinate Transformations

- Need general system for 2-d coordinate systems and transformations, including both spherical and Cartesian systems.
- Transforms must be composable; conceptually we have a graph with coordinate systems as nodes and transforms as edges.
- Needs close integration with geometry libraries.
- Needs very lightweight implementations of affine/linear transforms.
- Needs interoperability with Image xy0 concept.
- Needs serialization to both internal (round-trippable) formats and import/export to standard external formats. Ideally the internal format would also be at least somewhat external (i.e. shared with Astropy).
- Coordinate tranforms are not wavelength-dependent.
- See also DMTN-10.

9.22 Numerical Integration

- Standard basic numerical integration based on Gaussian quadrature: can probably just wrap an external library.
- Unclear whether we also need any differential equation integration.
- May need specialized routines for computing multivariate Gaussian and/or Student's T CDFs for Monte Carlo sampling.

9.23 Random Number Generation

- Just need standard distributions and generators provided by most external RNG libraries.
- Need to design carefully with parallelization primitives to ensure deterministic results when running in parallel.

9.24 Interpolation and Approximation of 2-D Fields

- Unified interface to spline, polynomial, inverse-distance approaches to representing 2-d fields.
- Used for at least backgrounds and aperture corrections, maybe PSF modeling, WCS, other things.

9.25 Pixel Interpolation

- Unified interface to spline, polynomial, inverse-distance approaches to representing 2-d fields.
- Used for at least backgrounds and aperture corrections, maybe PSF modeling, WCS, other things.

9.26 Common Functions and Source Profiles

- Library of 2-d functions used for PSFs and galaxy profiles. Sersics, Gaussians, Moffats, etc.
- Maybe delegate to GalSim (would probably require contributing required features to GalSim)?

9.27 Camera Descriptions

- What we call CameraGeom, but it's more than geometry.
- Geometry is built on top of Coordinate Transformations library.
- Electronic descriptions built on top of AmpInfo Tables.
- Throughput descriptions built on top of Chromaticity Utilities

9.28 Numerical Optimization

- Linear least-squares fitting with and without constraints, with and without Bayesian priors.
- At least some nonlinear fitting with and without Bayesian priors (extension of Levenberg-Marquardt probably). May need to handle some limited constraints as well.
- Could invest a lot of effort early in this and do it well; this would retire risk elsewhere. Or we can do this as-needed and probably spend less effort overall, but may find ourself blocked at inconvenient times by lack of hard-to-implement features.

9.29 Monte Carlo Sampling

- Need modern MCMC sampler. Could probably use external code, but it's not entirely clear we can afford to do this in Python.
- Need adaptive importance sampling from mixture distributions and MCMC chains.

9.30 Point-Spread Functions

- Includes aperture corrections.
- Includes characterization of extended wings of PSF.
- Wavelength-dependent.
- Must support coaddition of PSF models.
- May need know its uncertainty, and be able to sample PSF realizations form this.

10 Glossary

API Applications Programming Interface

CBP Collimated Beam Projector

CCOB Camera Calibration Optical Bench

CTE Charge Transfer Efficiency

DAC Data Access Center

DAQ Data Acquisition

DMS Data Management System

DR Data Release.

EPO Education and Public Outreach

Footprint The set of pixels that contains flux from an object. Footprints of multiple objects may have pixels in common.

FRS Functional Requirements Specification

MOPS Moving Object Pipeline System

OCS Observatory Control System

Production A coordinated set of pipelines

PFS Prime Focus Spectrograph. An instrument under development for the Subaru Telescope.

PSF Point Spread Function

QE Quantum Efficiency

RGB Red-Green-Blue image, suitable for color display.

SDS Science Array DAQ Subsystem. The system on the mountain which reads out the data from the camera, buffers it as necessary, and supplies it to data clients, including the DMS.

SDQA Science Data Quality Assessment.

SNR Signal-to-Noise Ratio

SQL Structured Query Language, the common language for querying relational databases.

TBD To Be Determined

Visit A pair of exposures of the same area of the sky taken in immediate succession. A Visit for LSST consists of a 15 second exposure, a 2 second readout time, and a second 15 second exposure.

VO Virtual Observatory

VOEvent A VO standard for disseminating information about transient events.

WCS World Coordinate System. A bidirectional mapping between pixel- and sky-coordinates.

References

[1] M. Ankerst, M. M. Breunig, H.-P. Kriegel and J. Sander, **OPTICS: Ordering Points To Identify the Clustering Structure**, Proc ACM SIGMOD (1999).

[2] P. Antilogus, P. Astier, P .Doherty, A. Guyonnet and N. Regnault **The brighter-fatter effect and pixel correlations in CCD sensors** Journal of Instrumentation, Volume 9, Issue 3, article id. C03048 (2014).

[3] A. Becker et al, **Report on Late Winter 2013 Production: Image Differencing** `http://ls.st/x9f`.

[4] A. Becker, **Report on Summer 2014 Production: Analysis of DCR**, `https://github.com/lsst-dm/S14DCR/blob/master/report/S14report_V0-00.pdf`.

[5] **An algorithm for precise aperture photometry of critically sampled images**, MNRAS 431, 1275–1285, 2013

[6] J. S. Bloom et al, **Automating discovery and classification of transients and variable stars in the synoptic survey era**, PASP 124, 1175–1196 (2012).

[7] J. F. Bosch, **Modeling Techniques for Measuring Galaxy Properties in Multi-Epoch Surveys**, PhD Thesis, University of California, Davis (2011). `http://adsabs.harvard.edu/abs/2011PhDT.....226B`

[8] J. Bosch, P. Gee, R. Owen, M. Juric and the LSST DM team, **LSST DM S13 Report: Shape measurement plans and prototypes**, `https://docushare.lsstcorp.org/docushare/dsweb/ImageStoreViewer/Document-15298`

[9] J. Bosch, **Measurement of Blended Objects in LSST**.

[10] **Optimal Time-Series Selection of Quasars**, ApJ 141, 93 (2011).

[11] **Automated Supervised Classification of Variable Stars I. Methodology**, A&A 475, 1159–1183 (2007).

[12] E. M. Huff et al, **Seeing in the dark – I. Multi-epoch alchemy**, `http://arxiv.org/abs/1111.6958`.

[13] H. Furusawa et al, **Hyper Suprime-Cam Survey Pipeline Description**, `http://hsca.ipmu.jp/pipeline_outputs.pdf`.

[14] M. J. Jee and J. A. Tyson, **Toward Precision LSST Weak-Lensing Measurement. I. Impacts of Atmospheric Turbulence and Optical Aberration**, PASP 123, 596(2011).

[15] M. J. Jee, J. A. Tyson, M. D. Schneider, D. Wittman, S. Schmidt and S. Hilbert, **Cosmic shear results from the Deep Lens Survey. I. Joint constraints on Ω_M and σ_8 with a two-dimensional analysis**, ApJ 765 74 (2013).

[16] J. Kubica et al, **Efficiently Tracking Moving Sources in the LSST**, Bulletin of the American Astronomical Society, 37, 1207 (2005).

[17] D. Lang, D. Hogg, S. Jester and H.-W. Rix, **Measuring the undetectable: Proper motions and parallaxes of very faint sources**, AJ 137 4400–4111 (2009).

[18] R. H. Lupton et al, **SDSS Image Processing II: The *Photo* Pipelines**. `http://www.astro.princeton.edu/~rhl/photo-lite.pdf`

[19] R. Lupton and Ž. Ivezić, **Experience with SDSS: the Promise and Perils of Large Surveys**, Astrometry in the Age of the Next Generation of Large Telescopes, ASP Conferences Series, Vol 338 (2005). `http://adsabs.harvard.edu/abs/2005ASPC..338..151L`

[20] R. Lupton, M. Jurić and C. Stubbs, **LSST's Plans for Calibration Photometry**, July 2015.

[21] L. Denneau, J. Kubica and R. Jedicke, **The Pan-STARRS Moving Object Pipeline**, Astronomical Data Analysis Software and Systems XVI ASP Conference Series, Vol. 376, proceedings of the conference held 15-18 October 2006 in Tucson, Arizona, USA. Edited by Richard A. Shaw, Frank Hill and David J. Bell., p.257.

[22] N. Padmanabhan et al, **An Improved Photometric Calibration of the Sloan Digital Sky Survey Imaging Data**, ApJ 674 1217–1233 (2008).

[23] A. Rasmussen, **Sensor Modeling for the LSST Camera Focal Plane: Current Status of SLAC Originated Code** July 2015. `https://docushare.lsstcorp.org/docushare/dsweb/Get/Document-8590`.

[24] J. Richards et al, **On Machine-learned Classification of Variable Stars with Sparse and Noisy Time-series Data**, ApJ 733 10 (2011).

[25] E. F. Schlafly et al, **Photometric Calibration of the First 1.5 Years of the Pan-STARRS1 Survey**, ApJ 756 158 (2012).

[26] Stetson, P.B., **On the Automatic Determination of Light-Curve Parameters for Cepheid Variables**, PASP 108 851–876 (1996).

[27] C. W. Stubbs, **Precision Astronomy with Imperfect Fully Depleted CCDs – An Introduction and a Suggested Lexicon**, Journal of Instrumentation, Volume 9, Issue 3, article id. C03032 (2014).

[28] A. S. Szalay, A. J. Connolly and G. P. Szokoly, **Simultaneous Multicolor Detection of Faint Galaxies in the Hubble Deep Field**, AJ 117 68–74 (1999).

[29] C. Alard and R. H. Lupton, **A Method for Optimal Image Subtraction**, ApJ 503, 1996 325–331 (1998).

[30] C. Alard, **Image subtraction using a space-varying kernel**, A&A 144, 2 363–370 (2000).

[31] , H. Israel, H., F. V. Hessman, and S. Schuh, **Optimising optimal image subtraction**, Astronomische Nachrichten 328, 16–24.

[32] N. Kaiser, **Addition of Images with Varying Seeing**, Pan-STARRS Document Control, PSDC-002-011-xx (2004).

[33] B. Zackay, E. O. Ofek, and A. Gal-Yam, **Proper image subtraction – optimal transient detection, photometry and hypothesis testing**, ApJ, *Submitted* (2016).