METADETECTION: MITIGATING SHEAR-DEPENDENT OBJECT DETECTION BIASES WITH METACALIBRATION

Erin S. Sheldon, 1 Matthew R. Becker, 2 Niall MacCrann, 3, 4 and Michael Jarvis 5

1 Brookhaven National Laboratory, Bldg 510, Upton, New York 11973, USA
2 High Energy Physics Division, Argonne National Laboratory, Lemont, IL 60439, USA
3 Center for Cosmology and Astro-Particle Physics, The Ohio State University, Columbus, OH 43210, USA
4 Department of Physics, The Ohio State University, Columbus, OH 43210, USA
5 Department of Physics and Astronomy, University of Pennsylvania, Philadelphia, PA 19104, USA

Abstract

METACALIBRATION is a new technique for measuring weak gravitational lensing shear that is unbiased for isolated galaxy images. In this work we test METACALIBRATION with overlapping, or “blended” galaxy images. Using standard METACALIBRATION, we find a few percent bias for galaxy densities relevant for current surveys, and that this bias increases with increasing galaxy number density. We show that this bias is not due to blending itself, but rather to shear-dependent object detection. If object detection is shear independent, no deblending of images is needed, in principle. We demonstrate that detection biases are accurately removed when including object detection in the METACALIBRATION process, a technique we call METADETECTION. This process involves applying an artificial shear to images of small regions of sky, and performing detection and measurement on the sheared images in order to calculate a shear response. We show that the method works up to second-order shear effects even in highly blended scenes. However, because the space between objects is sheared coherently in METADETECTION, the accuracy is ultimately limited by how closely this process matches real data, in which some, but not all, galaxies images are sheared coherently. We find that even for the worst case scenario, in which the space between objects is completely unsheared, the bias is at most a few tenths of a percent for future surveys. We show that the primary technical challenge for METADETECTION, deconvolution using a spatially varying point-spread-function, does not result in a significant bias for typical imaging surveys. Finally, we discuss additional technical challenges that must be met in order to implement METADETECTION for real surveys.

1. INTRODUCTION

Recently developed methods to estimate weak gravitational lensing shear can in principle provide calibration at the 0.1% level or better, sufficient for the requirements of future weak lensing surveys (e.g., Huterer et al. 2006). At the time of writing, two methods have demonstrated sufficient accuracy without reliance on calibration from simulations, including rigorous mathematical formalisms to deal with selection effects: the BFD method (Bernstein et al. 2016) and the METACALIBRATION method (Huff & Mandelbaum 2017; Sheldon & Huff 2017). However, the existing tests of BFD and METACALIBRATION, while stringent, did not include an important aspect of the real universe: the images of objects overlap on the sky and thus the light from separate objects is “blended” (for discussion of blending effects see, e.g., Dawson et al. 2016).

METACALIBRATION can, in principle, be used calibrate any shear measurement biases, even those associated with blending. However, we will show below that there is a particular calibration bias associated the process of detecting objects in the presence of blending, and this is not addressed in naive implementations of METACALIBRATION. This bias is especially large for ambiguous detections on highly blended images and thus poses a challenge for future lensing surveys in which blending will be important (Dawson et al. 2016).

At this stage it is worthwhile to define exactly what we mean by object detection. For isolated objects, object detection is closely related to the detection of regions of an image with pixel values above some threshold; this is perhaps the traditional meaning of the word detection. But when objects overlap on the sky, whether due to physical association or chance projection, there may be an additional desire to determine how many objects there are in each detected region. This may be desirable, for example, when assigning a redshift distribution to a set of detections. We associate this process with object detection. We reserve the term “deblending” to specifically mean the process of assigning a fraction of the light in each pixel to each detected object, which may or may not be a feature of the object detection. In this work, for the sake of brevity, we will use the terms “detection” and “object detection” interchangeably.

In the weak shear regime, the lensing mapping is one-to-one and preserves surface brightness (Schneider et al. 1992). For such a mapping, object detection need not be shear dependent. For example, an object detection algorithm that identifies connected regions in an image with pixel values above a threshold will not in principle be shear dependent. This is because the topology of the contours, or the number of closed contours, at a given surface brightness will not change under a shear, due to the preservation of surface brightness and the one-to-one nature of the mapping. However, in real observations the image resolution is degraded by a point-spread-function (PSF) due to the atmosphere, telescope optics and detector. In this case the overlap of objects, and also the topology of contours of a given surface brightness, does depend on shear because the PSF convolution occurs after the shear mapping. This effect is demonstrated in Figure 1. Thus the simple threshold object detection
method described above will manifest a shear-dependent object detection bias. Note this effect is present even in the absence of pixel noise.

Common object detection schemes in use today, such as those in SOURCE EXTRACTOR (Bertin & Arnouts 1996) and the HST/LSST pipelines (Bosch et al. 2018a,b) are based on thresholding, similar to the simple approach described above but differing in complexity and efficiency. The effective threshold used to divide regions into separate objects in these codes is not a simple threshold above noise, but is rather a relative quantity. This is demonstrated clearly for SOURCE EXTRACTOR in Bertin & Arnouts (1996) Figure 2. Thus we would expect object detections produced by such a code to also manifest shear dependence. A simple local peak finder, run on a smoothed image, has similar properties.

Published implementations of METACALIBRATION (e.g., Huff & Mandelbaum 2017; Sheldon & Huff 2017), when used with the common object detection schemes discussed above, are expected to exhibit shear-dependent object detection biases. These implementations of METACALIBRATION work by applying artificial shears to small "postage stamp" images, extracted from a larger image, for objects found during an independent object detection step, run before the application of METACALIBRATION, followed by a calculation of the response of an ellipticity measurement to the applied shear. This independent object detection will already manifest a shear-dependent object detection bias, and thus any shear applied when running METACALIBRATION does not properly reflect the full response to shear.

This shear-dependent object detection bias is a type of selection effect. Corrections for selection effects in a static catalog were already derived in Sheldon & Huff (2017), but that formalism implicitly assumes that the base catalog itself is unaffected by selection effects. Similarly, that formalism cannot work for objects near the object detection threshold, even for isolated objects, because the object detections needed for the corrections will, by definition, not be present in the catalog.

As we will demonstrate, object detection effects can be naturally incorporated into METACALIBRATION by shearing somewhat larger images, rather than small postage stamps, and re-running the object detection algorithm on each of the sheared images. In this process, ellipticity measurement biases, selection effects and object detection are all accounted for simultaneously. We call this technique METADETECTION.

Calibration with simulations is an alternative route being explored by the community (see, e.g., Fenech Conti et al. 2017; Mandelbaum et al. 2018). The idea is to use an uncalibrated ellipticity measurement, which can manifest a large shear bias (of order 10%) and unknown selection effects. The final shear measurements are then calibrated, including selection effects, using a simulation that matches the data as closely as possible. Ultimately METADETECTION may have some remaining biases that must be calibrated with simulations. Our goal in developing this algorithm is to make these biases as small as possible, sub-percent as opposed to 10 percent, which we expect will greatly reduce the sensitivity of the final calibration to small inaccuracies in the simulation.

The paper is laid out as follows. In Section 2, we describe our simulation and analysis techniques. In Section 3, we study the effects of object detection on shear measurements with METACALIBRATION. In Section 4, we describe METADETECTION which combines METACALIBRATION with an object detection algorithm in order to mitigate the shear biases from object detection. We also discuss the physical limits of METADETECTION there. In Section 5, we study the effects of the PSF variation on METADETECTION. Finally, we conclude in Section 7.

2. ANALYSIS AND SIMULATION TECHNIQUES

In this section, we describe our object simulation and measurement techniques. In all cases, we used the GALSIM (Rowe et al. 2015) software package to generate images, perform convolutions etc. We used the SEP (Barbary et al. 2017) Python wrapper of the SOURCE EXTRACTOR software package (Bertin & Arnouts 1996) for source detection as needed. Finally, we made extensive use of ngmix$^2$ for object measurement and the METACALIBRATION implementation.

2.1. METACALIBRATION

METACALIBRATION is a general technique that computes the linear response of image measurements to an applied shear using only the observed image. For a small applied shear $\gamma$, we can expand a measurement $e$ as

$$
e \approx e|_{\gamma=0} + \partial e \gamma|_{\gamma=0} + O(\gamma^2)$$

$$\equiv e|_{\gamma=0} + R\gamma + O(\gamma^2)$$

(1)

where $R$ is the response matrix of the image measurement at zero applied shear, $R_{ij} = \partial e_i / \partial \gamma_j$, with $i$ and $j$ taking all combinations of the two shear components. The measurement $e$ can be, for example, an ellipticity measurement, and in what follows we will use the term ellipticity without loss of generality.

We estimate the response using a numerical, finite-difference derivative

$$R_{ij} \approx \frac{e_i^+ - e_i^-}{\Delta \gamma_j}.$$  

(2)

where $R_{ij}$ is the estimated response of the measurement to shear and $\Delta \gamma_j = 2\gamma_j$ is the difference between two applied shears, $\pm \gamma_j$, with $\gamma_j$ a small shear, usually of order 0.01. The quantity $e_i^+$/$e_i^-$ is the $i$-th ellipticity component measured on an image sheared with $\pm \Delta \gamma_j$. The $e_i^+$/$e_i^-$ used in the finite differences measured on artificially sheared images (Sheldon & Huff 2017), the creation of which requires careful handling of the PSF and other observational effects. Note that as the estimated responses per-object are quite noisy, they must be averaged over many images/objects in order to estimate the response of a set of images/objects to a shear. We will expand this method to include object detection in section 4.

\footnote{An open question, which we will not address in this work, is whether it is possible to derive a shear-independent object detection algorithm in the presence of a PSF and a detector with finite spatial resolution. Such an algorithm would in principle eliminate the shear-dependent object detection biases explored in this work.}

\footnote{https://github.com/esheldon/ngmix/}
We will focus on detection biases in this work, but there are a number of steps in the image processing that are shear dependent: detection, centroiding, ellipticity measurement, flux measurement, etc. In this sense, the \textsc{metadetection} method will measure the response of all image manipulations and measurements to an applied, constant shear.

### 2.2. Multi-object Fitting Deblending

Multi-object Fitting (MOF) deblending is a technique employed by the Dark Energy Survey to account for blending of objects when performing image measurements (Drlica-Wagner et al. 2018). It is representative of a set of techniques that involve fitting models to images for a list of preexisting detections. The model fit is then used directly to form a flux measurement or indirectly by using it to approximately remove the light of the neighboring objects in the image before further processing.

In this work, we used an \texttt{ngmix} based MOF algorithm\(^3\). It is an improved version of the MOF fitter used in Drlica-Wagner et al. (2018) which is both more stable and faster. It uses a linear combination of a De Vaucouleurs’ (de Vaucouleurs 1948) profile and exponential profile. The profiles are constrained to be cocentric, coelliptical, and to have a fixed one-to-one size ratio. The relative amplitude of the two profiles, the fraction of the total flux in the De Vaucouleurs’ profile, is a free parameter and is allowed to vary outside of the range \([0, 1]\). Finally, to process a large number of objects, we followed Drlica-Wagner et al. (2018) and broke them up into associated groups. These groups of objects were then simultaneously fit using a least-squares loss function.

### 2.3. Galaxy Pair Simulations

In order to isolate the effects of detection easily, we employed a simulation setup consisting of two galaxies with a variable separation between them. We varied the separation of the objects in order to carefully tune the effects of blending.

The simulated galaxies were each a combination of a bulge component, modeled as a De Vaucouleurs’ profile (de Vaucouleurs 1948) and disk component modeled as an exponential. The fraction of light in the bulge was random and ranged uniformly between 0.0 and 1.0. The disk ellipticity was drawn from the distribution presented in Bernstein & Armstrong (2014), equation 24, with ellipticity variance set to 0.20, with a random orientation. The bulge was given the same orientation as the disk but with ellipticity set to the disk ellipticity times a random number drawn uniformly between 0.0 and 0.5. The half-light radius of the disk \(r_{50}^{\text{disk}}\) was set to a uniform random draw between 0.4 and 0.6 arcsec. The half-light radius of the bulge was a random draw between 0.4\(r_{50}^{\text{disk}}\) and 0.6\(r_{50}^{\text{disk}}\). The bulge was shifted from the center of the disk within a radius 0.05\(r_{50}^{\text{disk}}\) and in a random direction. The light of the disk was divided between a smooth component and a set of simulated “knots of star formation”, represented by point sources placed randomly with the same exponential distribution as the disk. Between 1 and 50 knots were placed, such that the fraction light in the knots ranged between 0.4\% and 20\%. The total flux and noise were set such that the signal-to-noise ratio ranged uniformly between 25 and 35. The models were convolved by a PSF modeled as a Moffat (Moffat 1969) profile with \(\beta = 2.5\) and full with at half maximum 0.9 arcseconds, and rendered into an image with pixel scale 0.263 arcseconds.

We rendered two of these randomly generated galaxies in an image, with separation ranging from 1.0 and 4.0 arcsec. The pair was situated such that the line between the pair had a uniform random orientation relative to the coordinate axes. Each object was given an additional random dither within a pixel. The galaxies were treated as transparent, such that the value in a pixel was equal to the total sum from both galaxies plus noise. Example images are shown in Figure 2.

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\(^3\) https://github.com/esheldon/mof/
2.4. Simulations with Representative Galaxy Density and Noise

We used the WeakLensingDeblending\(^4\) package to generate image simulations with realistic galaxy densities and pixel noise for both the DES and LSST surveys.

We generated images in the r-, i-, and z-bands with an effective depth that is roughly equivalent to full 5 and 10 year coadd image for the DES and LSST respectively. For our primary tests, we neglected the effects of PSF variation and used a constant PSF per-band with the typical (expected) seeing for each survey (∼1 arcsec and ∼0.8 arcsec respectively). We tested variable PSFs separately, as discussed in §5. For the DES image simulations, we modified the settings slightly such that the effective exposure time was equivalent to ten 90 second exposures. The depths of the LSST images were set to match those assumed by the WeakLensingDeblending package for the 10 year survey, although note the modifications below. In all simulations a shear of $\gamma_1 = 0.02$ was used.

We made two additional modifications to the simulations produced by this package. The galaxy models and PSFs were generated using the WeakLensingDeblending package, using its internal survey settings and object catalogs. But rather than using the package to render into an image, we rendered them separately so that we could control whether the full scene was sheared, including the space between objects, or just the objects were sheared (the only mode supported by WeakLensingDeblending).

We also multiplied the density of input sources by a factor of 0.45 and a factor of 0.4 for the DES-like and LSST-like simulations, respectively, in order to produce a realistic number density of detected sources. We also performed tests with the unmodified input catalog for the LSST-like simulations, in order to test with an extreme density. The detected source densities in these three simulations were approximately 35 per square arcmin for DES year 5, 75 per square arcmin for LSST year 10, and 140 per square arcmin with the unmodified source catalog for the LSST-like simulations. Example images for each survey are shown in Figure 3.

2.5. Measuring Shear Biases

We report our results in terms of the standard parameterization of shear measurement biases (see, e.g., Heymans et al. 2006)

\[
g \equiv c + (1 + m)\gamma
\]

where $g$ is the recovered shear, $c$ is the additive bias, and $m$ is the multiplicative bias. Below we report only $m$,
but we have found that $c$ is consistent with zero in all cases.

We used the technique of Pujol et al. (2019) to reduce the noise on measurements of $m$ in our simulations. This technique works as follows. We generated pairs of images with identical galaxy and noise properties, but with opposite true shears applied $\gamma_{\pm}$ (we use a scalar notation because the shear was only applied in one component). For each pair of simulations, we calculate the mean ellipticity and mean response. We then calculate ensemble means $\langle e_{\pm}\rangle$ and $\langle R \rangle = (\langle R_+ \rangle + \langle R_- \rangle)/2$ over all such pairs of images, and form a difference of the overall recovered shear that partially cancels noise:

$$\gamma_{\text{est}} = \frac{\langle e_+ \rangle - \langle e_- \rangle}{2 \langle R \rangle},$$

We then calculated $m$ using equation 3, $\gamma_{\text{est}}$ and the true input shear. We estimated the errors on the mean $m$ using bootstrap resampling of the set of image pairs, repeating the computation of $m$ for each bootstrap sample. We employed a similar procedure for $c$, except that we used the average of the two estimated shears so that any additive biases common to both simulations do not cancel. In all cases we measured $m$ using the 1-component of the shear and $c$ with the 2-component of the shear, though we have found this choice not to matter in explicit testing.

3. SHEAR-DEPENDENT DETECTION BIASES

In this section, we present results from a variety of specialized simulation setups to elucidate the role of detection biases in METACALIBRATION shear measurements. We first examine shear measurement on pairs of galaxies at various separations. We then study detection biases in DES- and LSST-like simulations with realistic galaxy densities and pixel noise. We find in all cases that object detection imparts a non-negligible shear measurement bias. As we will show in §4.1, we can correct this bias by including detection in the METACALIBRATION process, even if no explicit deblending (division of light between objects) is performed.

3.1. Bias in Simulations of Galaxy Pairs

We tested METACALIBRATION with MOF deblending using the galaxy pair simulation presented in §2.3. We used SOURCE EXTRACTOR for object detection, with settings matching those used for DES year 5 survey reductions (DES Collaboration, in prep.)5. We got similar results using a simple local peak finder for detection6. We also saw similar levels of bias with and without performing deblending using MOF.

The multiplicative bias $m$ is shown in Figure 4 as a function of the pair distance. For a large separation of 4 arcsec, two objects were detected in essentially all cases, but as the separation was decreased the detection became more ambiguous, with only one object detected in some cases. At 1.5 arcsec separation the detection was most ambiguous, with two objects detected in half the cases. As the separation was decreased further, one object was detected more often than two, and at 1.0 arcseconds only one object was detected in essentially all cases. For close separations the blend is unrecognized but the detection is unambiguous, in the sense that the detection algorithm consistently finds one object.

In the cases where the detection is unambiguous, at close and far separations, there is no bias in the recovered shear. But the bias increases as the detection becomes more ambiguous. The maximum bias occurs at 1.5 arcsec separation, where two objects detected in half the cases.

The correspondence between detection ambiguity and shear bias is a hint that the bias is caused by shear-
compared two different metametacalibration shear measurements. The first was performed on a catalog of the true source positions using a fixed 1.2 arcsecond Gaussian weighted moment ellipticity measurement. The second employed metametacalibration with the same ellipticity measurement, but using Source Extractor detections rather than the true object positions. We found that while the first metametacalibration shear measurement is unbiased (−0.0011 ± 0.0012), the second exhibits a bias of −0.058 ± 0.001.\(^8\) Note that this ellipticity measurement makes no corrections for object blending, but in the case where we use the true object positions, it is still unbiased. Thus we have demonstrated that given a set of true source locations, metametacalibration is not sensitive to blending.\(^9\)

This set of tests also demonstrates explicitly that source detection can cause significant shear measurement biases even for techniques which are robust to blending. The source detection biases probably originate from multiple causes, but one of those causes is certainly the merging or splitting of object detections in a way that is shear dependent, as illustrated with the toy example in Figure 1 and the galaxy pair tests above.

4. MITIGATING SHEAR-DEPENDENT DETECTION BIASES

In the previous section, we demonstrated that source detection is a significant source of bias in shear measurements with metametacalibration. Here we show we can mitigate this bias by including source detection in the metametacalibration process.

We generated relatively large images, \(\sim 2\) arcminutes on a side, and applied metametacalibration directly to the full image using the PSF at the center of the image for deconvolutions. We performed object detection on each of the five artificially sheared images (see \S 2.1) using Source Extractor. We then made measurements in postage stamps around each detection in each image using a non-PSF corrected, Gaussian-weighted moment. These five catalogs were then combined into a single estimate for the shear by computing the average shear response for the image

\[
\langle \gamma \rangle \approx \langle R \rangle^{-1} \langle e \rangle
\]

where the equation for the response above is for a single shear component. We term this process meta detection.\(^7\)

\(^7\) The bias numbers here are fairly noisy, but it is interesting to note that the bias for LSST year 10 is not very much larger than DES year 5, despite the fact that the galaxy density is about twice as high. This may be partly due to the better resolution of the LSST images: the area of the LSST PSF 60% smaller than DES PSF. Thus the images of small galaxies, at fixed density, will overlap less in LSST images than they do in DES images.

\(^8\) The simulations with the true source positions are computationally slow because they involve measurements on all sources, even ones which are undetectable. Thus we were unable to decrease the errors on the multiplicative bias below \(\sim 0.1\%\). However, for simulations with round, exponential, high signal-to-noise objects only, we have found that metametacalibration with the true source positions and a weighted moment has bias (0.00033 + / − 0.00009) in the presence of blending, consistent with the bias expected due to the breakdown of the weak lensing approximation.

\(^9\) In practice, we have found that when using metametacalibration with true detections and more complex ellipticity measurements, for example using a non-linear model fit, biases can enter at the few tenths of a percent level. Thus whether metametacalibration is unbiased when using true detections does depend on the technique used to measure ellipticities on the sheared metametacalibration images.
Multiplicative biases in weak lensing simulations for various shear measurement techniques. In all cases, the simulations use realistic galaxy ellipticities, galaxy sizes and noise for the given survey. For measurements using standard metacalibration with MOF deblending, a cut of $T/T_{PSF} > 0.5$ was also applied. Measurements with metadetection and moments used a size cut of $T/T_{PSF} > 1.2$. In the case of metadetection with moments, no deblending corrections are applied and the moments are a simple weighted moment with no PSF correction.

| Simulation | Method | Full Scene Sheared? | S/N Cut | m          |
|------------|--------|---------------------|---------|------------|
| DESY5      | metacal+MOF yes | $S/N > 10$ | $-0.036 \pm 0.005$ |
| DESY5      | metacal+MOF yes | $S/N > 15$ | $-0.023 \pm 0.004$ |
| DESY5      | metacal+MOF yes | $S/N > 20$ | $-0.015 \pm 0.004$ |
| LSSTY10    | metacal+MOF yes | $S/N > 10$ | $-0.035 \pm 0.002$ |
| LSSTY10    | metacal+MOF yes | $S/N > 15$ | $-0.031 \pm 0.002$ |
| LSSTY10    | metacal+MOF yes | $S/N > 20$ | $-0.026 \pm 0.002$ |
| LSSTY10 2× dens. | metacal+MOF yes | $S/N > 10$ | $-0.082 \pm 0.005$ |
| LSSTY10 2× dens. | metacal+MOF yes | $S/N > 15$ | $-0.067 \pm 0.005$ |
| LSSTY10 2× dens. | metacal+MOF yes | $S/N > 20$ | $-0.062 \pm 0.004$ |

| Simulation | Method | Full Scene Sheared? | S/N Cut | m          |
|------------|--------|---------------------|---------|------------|
| DESY5      | metadetect+moments yes | $S/N > 10$ | $+0.00025 \pm 0.00088$ |
| DESY5      | metadetect+moments yes | $S/N > 15$ | $-0.00085 \pm 0.00070$ |
| DESY5      | metadetect+moments yes | $S/N > 20$ | $+0.00024 \pm 0.00061$ |
| LSSTY10    | metadetect+moments yes | $S/N > 10$ | $+0.00084 \pm 0.00061$ |
| LSSTY10    | metadetect+moments yes | $S/N > 15$ | $-0.00001 \pm 0.00047$ |
| LSSTY10    | metadetect+moments yes | $S/N > 20$ | $+0.00042 \pm 0.00039$ |
| LSSTY10 2× dens. | metadetect+moments yes | $S/N > 10$ | $+0.00047 \pm 0.00043$ |
| LSSTY10 2× dens. | metadetect+moments yes | $S/N > 15$ | $-0.00002 \pm 0.00034$ |
| LSSTY10 2× dens. | metadetect+moments yes | $S/N > 20$ | $+0.00019 \pm 0.00028$ |

| Simulation | Method | Full Scene Sheared? | S/N Cut | m          |
|------------|--------|---------------------|---------|------------|
| DESY5      | metadetect+moments no | $S/N > 10$ | $-0.0042 \pm 0.0009$ |
| DESY5      | metadetect+moments no | $S/N > 15$ | $-0.0052 \pm 0.0006$ |
| DESY5      | metadetect+moments no | $S/N > 20$ | $-0.0059 \pm 0.0006$ |
| DESY5 2× dens. | metadetect+moments no | $S/N > 10$ | $-0.0029 \pm 0.0006$ |
| DESY5 2× dens. | metadetect+moments no | $S/N > 15$ | $-0.0017 \pm 0.0005$ |
| DESY5 2× dens. | metadetect+moments no | $S/N > 20$ | $-0.0023 \pm 0.0005$ |
| LSSTY10    | metadetect+moments no | $S/N > 10$ | $-0.0015 \pm 0.0007$ |
| LSSTY10    | metadetect+moments no | $S/N > 15$ | $-0.0013 \pm 0.0006$ |
| LSSTY10    | metadetect+moments no | $S/N > 20$ | $+0.0001 \pm 0.0005$ |
| LSSTY10 2× dens. | metadetect+moments no | $S/N > 10$ | $-0.0047 \pm 0.0006$ |
| LSSTY10 2× dens. | metadetect+moments no | $S/N > 15$ | $-0.0035 \pm 0.0004$ |
| LSSTY10 2× dens. | metadetect+moments no | $S/N > 20$ | $-0.0029 \pm 0.0004$ |

Note that the averages above are over the catalogs from running source detection and ellipticity measurement on differently sheared images. This is in effect the “total derivative” response, shown in section 3 of Sheldon & Huff (2017), without any attempt to split the response into the shear response and selection response using the chain rule. Shear responses for individual detected objects, as used in both Sheldon & Huff (2017) and Huff & Mandelbaum (2017), were not calculated. Doing so would require matching the lists of detections found on the different sheared images, so that finite differences for each object could be formed. This act of matching would introduce the very shear-dependent object detection biases we wish to calibrate. We will discuss the implications of this fact for the analysis of imaging surveys in §6.

4.1. Results for Simulated Galaxy Pairs

In Figure 4 we show results for the simulations of galaxy pairs, now including detection in the metacalibration process. The blue filled circles represent the case where deblending is performed using MOF. The green plus signs represent the case where no deblending was performed. For the case without deblending, we further simplified the process; we calculated simple weighted moments at the position determined by SOURCE EXTRACTOR using a fixed weight function with full-width at half maximum 1.2 arcsec, without any correction for the PSF.

In both cases the bias is greatly reduced, with significant bias seen only at the special separation of 1.5 arcsec, where the two objects are detected as one object by SOURCE EXTRACTOR in half of the cases. This demon-
strates that the bias we see is not primarily due to the process of deblending itself, but rather shear-dependent detection effects. The remaining biases at 1.5 arcsec tend to be different sign for the deblended and non-deblended cases, which shows there is a qualitative difference in how the two measurements respond to the shear. As we will show below, we find no significant net bias for more realistic DES and LSST-like images where the typical separation of galaxies is not at a special value of maximum detection ambiguity.

4.2. Results for Simulations with Representative Galaxy Density and Noise

We show results for DES-like and LSST-like surveys in Table 1. We have used a constant PSF and constant shear for these simulations. We find that in all cases our METADETECTION shear measurements are unbiased up to second-order shear effects (we expect a bias of a few parts in 10000 for shears of 0.02, see Sheldon & Huff 2017). This conclusion holds despite the extensive blending of the object images and the large source detection effects we documented above. They also meet or exceed the requirements for analyzing an LSST-like survey (e.g., Huterer et al. 2006). Finally, note that we have also shown results for an LSST-like survey where the number density of objects is approximately twice that expected from the actual survey. Even at these higher densities we find no increase in the shear bias.

4.3. Testing the Physical Assumptions Behind METADETECTION

Here we address a key physical assumption made by METADETECTION, namely that the space between all objects is sheared coherently. With METADETECTION we shear the entire image, so the space between object is sheared as well as their shapes, and this is completely coherent across the image. In §4.2 we showed that, when the shear in the simulation matches this procedure exactly, we calculate the response accurately.

But real data typically contains images of objects sheared by different amounts at different redshifts, and can be thought of as a sum of a series of constant, but differently sheared images. In such an image, the shearing is not completely coherent. Variable shear itself is not a source of bias for METADETECTION; the formalism presented in (Sheldon & Huff 2017) recovers the mean shear or other ensemble statistic for a population. But because the shearing of the space between objects in real data is not completely coherent, we may expect that the part of the METADETECTION response associated with detection is slightly biased.

In Figure 5 we show a toy example, similar to Figure 1, demonstrating the extreme and unphysical case of two objects that are in line-of-sight projection but sheared completely independently. We did not allow the space between objects to be sheared. The contours of constant surface brightness differ less after shear than those shown in 1. This is intuitive, because the relative separation between objects does not change. The METADETECTION process of shearing the full image, which does move the positions of objects, will over-predict the response in this case.

In general, we expect a larger bias due to this effect for surveys with more object blending, which scales with object density and PSF size. To test these expectations, we created a set of simple simulations in which we sheared the shapes of objects, but not the space between objects. We simulated round galaxies with exponential light distributions and a half-light-radius of 0.5 arcsec. We then tested the accuracy METADETECTION shear recovery under varying conditions, namely with either 45 objects per square arcmin or 140 objects per square arcmin, and with either a 0.9 arcsec Gaussian PSF or a 1.1 arcsec Gaussian PSF. Our results are reported in Table 2 and confirm these expectations. However, we don’t expect these results to be representative of realistic scenarios.

In order to obtain an upper bound on this effect for real surveys, we made a simple modification to our simulations with realistic galaxy density and noise. When building them, rather than shearing the full scene to impart the true shear to the image, we sheared each object individually and then added it to the image, without any change in the object position. This modification leaves the space between objects unsheared, which is maximally different from what happens during the METACALIBRATION image shearing process.

Results for our more realistic survey simulations are in the bottom rows of Table 1. We found small residual biases in this case, of order $\sim 0.3\%$. While the fact that we find more bias for a DES-like survey than an LSST-like survey can be explained by the large PSFs in the DES-like survey and the smaller pixel scale in the LSST-like survey, some of the DES-like results are puzzling. In particular, the trend with object density in the DES-like surveys appears to be opposite our naive expectation. We do not fully understand this effect. While predicting the expected level of this bias for experiments such as such as DES and LSST is essential, it is beyond the scope of this work.

5. HANDLING PSF VARIATION

In order to apply METADETECTION to a real, multi-band, multi-epoch survey like the DES or LSST, we must address realistic levels of PSF variation, missing data, and non-trivial WCS transformations. We will address missing data and WCS issues in a future work, currently in preparation. Here we address the issue of PSF variation, which is technically the most challenging because METADETECTION requires deconvolution by the PSF over relatively large regions of sky.

The deconvolution of a spatially varying PSF formally
requires a spatially varying kernel, the implementation of which would be computationally challenging. We instead adopted efficient FFTs for deconvolution, which require a constant kernel. For this kernel, we chose to use the PSF associated with the center of the final coadd image, which is thus systematically wrong at other locations and will necessarily produce a bias in the recovered shear. However, we will show that the image coadding process used in a realistic multi-epoch survey results in a more uniform PSF in the final coadd, and sufficiently reduces associated biases.

For these simulations, we used a simple population of galaxies that have exponential profiles with a half light radius of 0.5 arcsec. All of the objects were round and were rendered at a signal-to-noise ratio greater than 20. These simulations had very low ellipticity noise and so could reach a high precision with a relatively small number of images. We created the images for the simulation by coadding a number of images with random, variable PSFs. **Metadetection** was then performed using the coadd of PSF models from the input images, with the PSF from each input image generated at the location of the center of the final coadd.

In order to place an upper bound on this effect, we created a variable PSF model that had significantly more variation than we expect in real data. See Appendix A for details. Using a single PSF realization from Appendix A, without coadding, we found a multiplicative bias of $-0.0065 + / -0.00044$. However, when coadding thirty of these models, which is the expected number of epochs for three bands in the final DES data set, we found a multiplicative bias of only $-0.00035 + / -0.00037$. For LSST many more epochs will be available for coadding. While this test is not conclusive, we expect that in a realistic survey scenario, PSF variation will not be a fundamental limitation for **metadetection**.

6. IMPLICATIONS FOR THE ANALYSIS OF IMAGING SURVEYS

The fact that five separate catalogs must be used without any attempt at matching them (see §4), has implications for using **metadetection** in the analysis of surveys. Typically a single reference or “gold” sample of objects is constructed and used for all subsequent calculations, such as calculating redshift distributions. With **metadetection**, multiple such catalogs, one for each artificial shear, must be constructed in order to understand the response of summary statistics to shear. Specifically, the process of selecting objects, such as removing objects with low signal-to-noise ratio or sorting objects into redshift bins, must be repeated using the measurements made on sheared images in order to include selection effects (Sheldon & Huff 2017).

When calculating sums and averages for other, non-shear quantities, such as a redshift distribution, the appropriate object-by-object weight is the shear response (Sheldon & Huff 2017). But individual responses cannot be calculated with **metadetection**, because this would require matching the catalogs produced from the different artificially sheared images, which would introduce shear-dependent selection effects. It may be possible to derive an appropriate mean weight using ensemble statistics. For example, one could define fine redshift bins (different from the bins used for tomography) and calculate the mean response in those bins using the separate sheared versions of the catalogs. This could then be interpolated to provide weights for objects when constructing the redshift distribution in tomographic bins. We will study this issue in more detail in a future work.

7. SUMMARY

In this work, we explored how **metacalibration** weak lensing measurements perform in scenarios where the images of objects overlap and the detection of objects can be ambiguous. These conditions will characterize all future weak lensing surveys, especially those executed beneath the atmosphere where PSF smearing significantly increases the blending of images, so accurate performance in this regime is critical. We find that **metacalibration** used with MOF-like object deblending techniques has many percent biases that get worse as the degree of blending increases. We then demonstrated that we can eliminate these biases at high precision by including the detection of objects in the **metacalibration** process, even for an LSST-like survey. We call this technique...
METADETECTION.

We tested an important assumption of METADETECTION, that the space between objects in an image is sheared coherently, an assumption that does not perfectly match real data. We placed an upper bound on the bias associated with this effect at a few tenths of percents for future surveys. More detailed study will be needed to predict the actual effect for specific data sets.

In future work we must address a number of technical challenges associated with implementing METADETECTION on real data. We must run METADETECTION over relatively large images ($\sim 1 - 2$ arcminutes on a side) in order efficiently capture ambiguities in the detection of objects. Detection is less efficient in smaller images, because the larger perimeter to area ratio results in a higher fraction of objects, including blends, near the edge. Also, over these large scales, the assumption that the PSF and world coordinate system (WCS) transformations are approximately constant will fail, complicating the application of an artificial shear. We have shown in this work that PSF variation is unlikely to be a problem when coadding many tens of images. However, in order to reconstruct accurate PSF models for the coadd, the input images can have no edges within the coadd region. This requirement means some images must be left out of the coadd process, resulting in some loss of some precision (Armstrong, R., et al. 2020). Finally, we should be able to handle non-constant WCS transformations by coadding the images into a nearly constant WCS, but this procedure remains to be tested.

Additional issues arise from masking. Large regions of images can have non-trivial masking patterns due to stellar diffraction spikes, streaks from moving objects, cosmic rays, etc. In the implementation presented in this work, we use fast Fourier transforms (FFTs) to handle convolutions. The FFT does not permit missing data, so the masked regions must be interpolated in some way. Care must be taken that this interpolation does not introduce a spurious shear signal. Compensating masks, rotated at right angles to the real masks, must be used in addition to the real mask in order to restore symmetry to the image (Sheldon & Huff 2017). Also, interpolation correlates the noise in the image, as does the coadding process itself, so the noise field used for correcting correlated noise effects must also be propagated through the same coadding and interpolation (Sheldon & Huff 2017; Armstrong, R., et al. 2020).

Finally, the five separate METADETECTION catalogs must each be incorporated into the full set of downstream analysis tasks (e.g., photometric redshift estimation, the construction of summary statistics, etc.) in order to be used for cosmological constraints. The procedures for doing this cannot match the catalogs to each other or any external catalog. Any matching of this nature would reintroduce detection biases. The procedures also must apply the same selection criterion to each of the five catalogs in order to properly measure the shear response. These restrictions may have important downstream effects on the analysis.

APPENDIX

A. FAST APPROXIMATE VARIABLE PSF MODELS

In this work we used a fast, approximate variable PSF model. This model eases the computational requirements for the simulations while also retaining the essential features of realistic PSF variation. In this appendix, we present the model and verify its statistical properties against more realistic PSF models.

We began with the results of Heymans et al. (2012). The degree to which these technical challenges can be overcome will ultimately determine the accuracy of METADETECTION when used to analyze imaging survey data.

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They fit the von Kármán model of atmospheric turbulence

\[ P(\ell) \propto \left( \ell^2 + \frac{1}{\theta_0^2} \right)^{-11/6} \]

to images with high stellar density. Here \( \theta_0 \) is the outer scale of turbulence. (Heymans et al. 2012) find that \( \theta_0 \approx 3 \) arcmin. We further added an additional Gaussian truncation of the power

\[ P_{\text{trunc}}(\ell) \propto P(\ell) \exp \left( -\ell^2 r^2 \right) \]
at a scale of \( r = 1 \) arcsec in order to reduce the level of resulting PSF variation. Below we show that even with this modification, our models still have more power than a realistic model for a survey, making them useful for providing upper limits on the effects of PSF variation.

Using this model, we seeded equal amounts of E- and B-mode power on a grid of 128 \( \times \) 128 cells using random phases. Each cell of the grid was one arcsec in size. We normalized the overall ellipticity variance to 0.10\(^2\). We then used the \( g_1 \) and \( g_2 \) components of this model to set the variation of the ellipticity of the PSF. We drew the mean ellipticity for each image from a Gaussian distribution of variance 0.10\(^2\). Note that we also bound the total ellipticity to at most 0.5. We modeled the PSF profile as a Moffat with shape parameter \( \beta = 2.5 \). The size of the Moffat profile was set to be proportional to \( \mu^{-3/4} \), where \( \mu \) is the magnification computed from the power spectra realization. The proportionality constant was drawn randomly from a log-normal model with scatter 0.1 arcmin and a central value set so the final PSF size mimicked a DES-like survey, with focal plane averaged FWHM \( \sim 1.1 \) arcsec.

We show an example PSF for a DES-like survey in Figure A1. Over a 1 square arcminute patch, our approximate models generate PSF ellipticity and size variation that are \( \geq 10 \times \) that seen in real 90 second exposures with DECam (Zuntz et al. 2018), or the expected variation in a 15 second exposure with LSST (Jee & Tyson 2011) over similar scales. Figure A2 shows the \( \xi_\pm \) shear correlation functions averaged over 100 realizations of our models. For comparison, we expect at most shear correlation function amplitudes of \( \sim 10^{-4} \) for LSST (Jee & Tyson 2011) and for DESCam 90 second exposures. The DECam models were generated using the methods of Jee & Tyson (2011) but for DECam-like environmental conditions. For the optical contributions to the PSF, we use a set of randomly drawn aberrations (similar to GREAT3 (Mandelbaum et al. 2014)), but with values more typical of DECam observations\(^\text{10}\).

\textsuperscript{10} https://github.com/GalSim-developers/GalSim/blob/releases/2.1/examples/great3/cgc.yaml
Figure A1. Variable PSF model statistics for a DECam-like exposure. The top-left panel shows the variation in the FWHM in arcseconds. The top-right panel shows a visualization of the PSF ellipticity variation. The bottom-left panel shows the variation in the 1-component of the PSF ellipticity. The bottom-right panel shows the variation in the 2-component of the PSF ellipticity. The variation in this model is $\gtrsim 10 \times$ larger than the typical PSF variation for either DECam or expected LSST observations. The pixel scale is 0.263 arcsec so that each panel is approximately 1 arcmin on a side.

Figure A2. Variable PSF model shear correlation functions for a DECam-like exposure. LSST is expected to have shear correlation function magnitudes around $\sim 10^{-4}$ (Jee & Tyson 2011).