SIMULATIONS OF WIDE-FIELD WEAK-LENSESING SURVEYS. II. COVARIANCE MATRIX OF REAL-SPACE CORRELATION FUNCTIONS

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ABSTRACT

Using 1000 ray-tracing simulations for a Λ-dominated cold dark model in Sato et al., we study the covariance matrix of cosmic shear correlation functions, which is the standard statistics used in previous measurements. The shear correlation function of a particular separation angle is affected by Fourier modes over a wide range of multipoles, even beyond a survey area, which complicates the analysis of the covariance matrix. To overcome such obstacles we first construct Gaussian shear simulations from the 1000 realizations and then use the Gaussian simulations to disentangle the Gaussian covariance contribution to the covariance matrix we measured from the original simulations. We found that an analytical formula of Gaussian covariance overestimates the covariance amplitudes due to an effect of the finite survey area. Furthermore, the clean separation of the Gaussian covariance allows us to examine the non-Gaussian covariance contributions as a function of separation angles and source redshifts. For upcoming surveys with typical source redshifts of \( z_s = 0.6 \) and 1.0, the non-Gaussian contribution to the diagonal covariance components at 1 arcmin scales is greater than the Gaussian contribution by a factor of 20 and 10, respectively. Predictions based on the halo model qualitatively well reproduce the simulation results, however show a sizable disagreement in the covariance amplitudes. By combining these simulation results we develop a fitting formula to the covariance matrix for a survey with arbitrary area coverage, taking into account effects of the finiteness of survey area on the Gaussian covariance.

Key words: gravitational lensing: weak – large-scale structure of universe – methods: numerical

Online-only material: color figures

1. INTRODUCTION

Weak gravitational lensing by intervening large-scale structure, the so-called cosmic shear, provides a powerful probe of dark matter and dark energy. Since its first detections by various groups (Bacon et al. 2000; Kaiser et al. 2000; Van Waerbeke et al. 2000; Wittman et al. 2000), substantial progress has been made on both theoretical and observational sides (e.g., Hamana et al. 2003; Massey et al. 2005; Jarvis et al. 2006; Semboloni et al. 2006; Fu et al. 2008; Schrabback et al. 2010). Weak lensing has the highest potential to constrain properties of dark energy among other cosmological observations, such as Type Ia supernovae (e.g., Riess et al. 1998; Perlmutter et al. 1999; Hicken et al. 2009), baryon acoustic oscillations (e.g., Eisenstein et al. 2005; Okumura et al. 2008), galaxy clusters (e.g., Vikhlinin et al. 2009; Mantz et al. 2010), if the systematic errors are well under control (Albrecht et al. 2006, 2009; Joudaki et al. 2009). The growth rate of mass clustering can be measured by “lensing tomography” (e.g., Hu 1999; Huterer 2002; Takada & Jain 2004) which in turn provides tight constraints on the equation of state of dark energy. For this purpose, a number of ambitious wide-field surveys have been proposed, such as Subaru Hyper Suprime-Cam Survey (Miyazaki et al. 2006), the Panoramic Survey Telescope & Rapid Response System (Pan-STARRS\textsuperscript{5}), the Dark Energy Survey (DES\textsuperscript{6}), the Large Synoptic Survey Telescope (LSST\textsuperscript{7}), the Wide-Field Infrared Survey Telescope (WFIRST\textsuperscript{8}), and Euclid (Refregier et al. 2010).

To attain the full potential of upcoming lensing surveys, it is essential to analyze data with appropriate statistical methods as well as to use sufficiently accurate theoretical models for the power spectrum and/or two-point correlation function and for the covariance matrix (e.g., Hikage et al. 2011 for a recent development of lensing power spectrum measurement method). Most of the useful cosmological information contained in the cosmic shear signal lies in small scales that are affected by nonlinear clustering. Therefore, non-Gaussian errors can be significant in weak-lensing measurements as indicated by several studies (White & Hu 2000; Cooray & Hu 2001; Semboloni et al. 2007; Doré et al. 2009; Eifler et al. 2009; Sato et al. 2009; Takada & Jain 2009; Lu et al. 2010; Pielorz et al. 2010; Seo et al. 2011) and also may cause biases in the best-fit parameters (Hartlap et al. 2009; Ichiki et al. 2009). Furthermore, future high-precision measurements may require adequate statistical methods, i.e., accurate likelihood function, of weak lensing in estimating cosmological parameters (Sato et al. 2010, 2011).

In the first paper of a series of our works (Sato et al. 2009), we studied the non-Gaussian effects on the covariance matrix of the cosmic shear power spectrum using 1000 realizations of ray-tracing simulations. In this paper, we study the non-Gaussian effects on the covariance matrix of the cosmic shear correlation function which is the most conventionally used statistical method in previous measurements.

\textsuperscript{5} http://pan-starrs.ifa.hawaii.edu/public/
\textsuperscript{6} http://www.darkenergysurvey.org/
\textsuperscript{7} http://www.lsst.org/
\textsuperscript{8} http://wfirst.gsfc.nasa.gov/
This paper is organized as follows. In Section 2, we briefly review the basics of the cosmic shear correlation function and its covariance. In Section 3, we show the main results and develop the fitting formula to compute the covariance matrix of cosmic shear correlation functions for a survey of arbitrary area. Section 4 is devoted to conclusion. Throughout the present paper, we adopt the concordance ΛCDM model with matter density \( \Omega_m = 0.238 \), baryon density \( \Omega_b = 0.042 \), dark energy density \( \Omega_k = 0.762 \) with equation of state parameter \( w = -1 \), spectral index \( n_s = 0.958 \), the variance of the density fluctuation in a sphere of radius \( 8 \ h^{-1} \) Mpc \( \sigma_8 = 0.76 \), and Hubble parameter \( h = 0.732 \). These parameters are consistent with the Wilkinson Microwave Anisotropy Probe (WMAP) three-year results (Spergel et al. 2007). In our ray-tracing simulation, each realization has an area of 25 deg\(^2\). The detailed description of our ray-tracing simulations is described in Sato et al. (2009).

2. PRELIMINARIES

2.1. Real-space Correlation Function and Its Covariance Matrix

In this section, we briefly review definitions of the cosmic shear correlation function and its covariance matrix.

Since the shear field is a spin-2 field, the field at one particular point on the sky carries two degrees of freedom. We can thus define different correlation functions from the measured shear field. The most conventionally used functions are given in terms of the lensing power spectrum as (e.g., Schneider et al. 2002; Munshi et al. 2008)

\[
\xi_+ (\theta) = \int_0^\infty \frac{dl}{2\pi} P_\kappa(l) J_0(l\theta), \tag{1}
\]

\[
\xi_- (\theta) = \int_0^\infty \frac{dl}{2\pi} P_\kappa(l) J_2(l\theta), \tag{2}
\]

where \( P_\kappa(l) \) is the convergence power spectrum (see, e.g., Bartelmann & Schneider 2001; Van Waerbeke & Mellier 2003, for the definition) and \( J_0(\cdot) \) and \( J_2(\cdot) \) are the zeroth and fourth-order Bessel functions, respectively. Observationally, \( \xi_+ (\theta) \) can be measured by averaging the product of ellipticity components over all the galaxy pairs that are separated by the angle \( \theta \) (also see Appendix A).

In reality, the measured \( \xi_+ \) and \( \xi_- \) are contaminated by systematic errors. Hence it is in practice useful to decompose the measured \( \xi_+ \) and \( \xi_- \) to the lensing-induced \( E \)-mode (gradient-mode) correlation function or equivalently the correlation function of the convergence field, \( \xi_{\kappa} (\theta) \). Another independent \( B \)-mode correlation function can be used to monitor residual systematic errors. Although \( \xi_+ \) and \( \xi_- \) contain theoretically equivalent information in the absence of systematic errors, which both have the same expression in terms of \( P_\kappa \) (Equation (1)), the two show a slight difference when measured from a finite-area survey or simulations as we will show below in detail. The difference is ascribed to the fact that the convergence is the projected mass density field, while the shear field is a quantity arising from the non-local tidal field that is affected by the mass distribution outside survey area or simulation area. Therefore in this paper we focus on \( \xi_+ \), rather than \( \xi_- \), to study the covariance matrix as the shear field is a more direct observable from actual data.

In Figure 1 we compare the correlation function \( \xi_+ (\theta) \) measured from the shear field in 1000 ray-tracing simulations (see Sato et al. 2009 for the details of simulations) with analytical predictions. To obtain the analytical predictions we first need to compute the lensing power spectrum \( P_\kappa (l) \), which is given as a projection of the mass power spectrum weighted with the radial lensing kernel along the line of sight based on Limber’s approximation:

\[
P_\kappa (l) = \int_0^{z_s} dz W_G(z, z_s) P_\delta \left( \frac{l}{\chi(z)} ; z \right), \tag{3}
\]

where \( W_G (z, z_s) \) is the lensing weight function (see Equation (9) in Sato et al. 2009) and \( P_\delta (k) \) is the mass power spectrum. We use the HaloFit fitting formula (Smith et al. 2003) to compute the nonlinear mass power spectrum \( P_\delta (k) \) for the cosmological model we have assumed. In Figure 1 we show the two analytical predictions. One is denoted by the solid curve showing the prediction computed based on the conventional method; the two-point correlation function \( \xi_+ (\theta) \) is computed by inserting the lensing power spectrum, computed from Equation (3), into Equation (1). The other is denoted by the dashed curve, where we properly take into account the fact that \( N \)-body simulations used in ray-tracing simulations do not contain density perturbations with length scales beyond the simulation box (see Sato et al. 2009 for details of the simulations). For this purpose we imposed \( P_\delta (k ; z) = 0 \) at \( k < k_t \) and at each lensing redshift \( z \) computing the lensing power spectrum (Equation (3)), where \( k_t \) is the fundamental mode of \( N \)-body simulation and given in terms of simulation box size \( L \) as \( k_t = 2 \pi / L \). Note that, since our ray-tracing simulations are done in a light-cone configuration along the line of sight, some large-length modes are indeed beyond the area of ray-tracing simulations.

Figure 1 shows that the two analytical predictions are in good agreement with the simulation results at small separations. However, the prediction (solid curve) including all the modes beyond the simulation box overestimates the simulation results at large separations, \( \theta \gtrsim 10' \). On the other hand, the dashed curve, which includes only a finite box-size effect of the
modes, better reproduces the simulation results at the large separations, up to $\theta \simeq 100'$. Thus, these results imply that the two-point correlation function of a given separation angle is affected by a wide range of Fourier modes due to the non-local integration relation between the real- and Fourier-space modes. In particular, even if focusing on the correlation functions at large separations in the linear regime, we need to properly take into account the effect of the density perturbations beyond the survey area, which cannot be observed. It is also worth noting that, if we impose the cutoff on multipole rather than the three-dimensional wavenumber, e.g., including only the multipole modes at $l > l_{\text{cut}} = 72$ corresponding to the largest angular mode of our simulated area 25 deg$^2$, the theoretical prediction underestimates too much the simulation result at large separation angles.

The results in Figure 1 can be compared with the result of our previous paper (Sato et al. 2009), where we compared the simulation and HaloFit results for the convergence power spectrum (see Figure 2 of the paper). The scale dependence of the disagreement is qualitatively different between real and Fourier space, reflecting the fact that the correlation function and the power spectrum is related to each other via the convolution. From various numerical tests we found that the shear correlation function remains accurate down to $\theta_{\text{min}} \simeq 0.5$ arcmin.

Next we move on to the covariance matrix of shear correlation function. The covariance matrix describes how the correlation functions of different separation angles are correlated with each other. Following the methods developed in Joachimi et al. (2008) and Takada & Jain (2009), the covariance matrix for the correlation function $\xi_\theta(\theta)$ is expressed as

$$\text{Cov}[\xi_\theta(\theta), \xi_\theta(\theta')] = \frac{1}{\pi \Omega_s} \int_0^\infty l d J_0(l\theta) J_0(l\theta') P_\xi(l)^2 + \frac{1}{4\pi^2 \Omega_s} \int_0^\infty l d l' \int_0^\infty l' d l'' J_0(l\theta) J_0(l'\theta') \tilde{T}_\xi(l, l'),$$

where $\Omega_s$ denotes the survey area and $\tilde{T}_\xi$ denotes the angle-averaged lensing trispectrum. Note that we ignored the shot noise contribution due to random intrinsic ellipticities. The derivation of Equation (4) assumes an ideal survey geometry; in other words Equation (4) is approximately valid only for the case, $\theta, \theta' < \sqrt{\Omega_s}$, and for large area surveys such as $\Omega_s \gtrsim 1000$ deg$^2$, as discussed in Appendix A in detail. Therefore, it is expected that for a small survey area the covariance matrix deviates from the above formula. We will call it the finite-area effect, which is examined in Appendix A. See Joachimi et al. (2008) for expressions of other covariance matrices $\text{Cov}[\xi_\theta(\theta), \xi_\theta(\theta')]$ and $\text{Cov}[\xi_\theta(\theta), \xi_{\theta'}(\theta')]$, which are examined in Section 3.2.

The first term in Equation (4) describes the Gaussian contribution, while the second term is the non-Gaussian contribution. There is an important difference between the covariance of the convergence power spectrum and that of the real-space correlation function. Even for a pure Gaussian field, the first term in Equation (4) is non-vanishing for the off-diagonal components with $\theta \neq \theta'$. The correlation functions of different separations are always correlated with each other. Also note that the covariance does not depend on the bin width of angles. Thus, when using the correlation function measurements for constraining cosmological parameters, it is very important to have an accurate model of the covariance matrix in order to properly interpret the measurement. We will use Equation (4) to compare the analytical prediction with the covariance measured from the simulations.

2.2. Constructing a Gaussian Field from the Simulations

The main goal of this paper is to quantify the relative importance of the non-Gaussian covariance to the Gaussian covariance as a function of angular scales and source redshifts. To address this, we first construct a Gaussian field using the ray-tracing simulations in order to separate out the Gaussian covariance contribution. We will hereafter call the constructed maps “the simulated Gaussian fields.” The reason why we use the simulated Gaussian fields instead of using the analytical prediction (the first term of Equation (4)) is as follows. First, the ray-tracing simulations do not include large-scale modes beyond the simulation box size. Second, as we will show below in detail, the covariance measured from the Gaussian simulations shows a nontrivial dependence on the survey area that cannot be fully described by the first term of Equation (4).

We generated the Gaussian simulations according to the procedures below. First, we Fourier-transformed each convergence field of 1000 ray-tracing simulations. Second, we make a Gaussian field by randomly selecting each Fourier mode from the Fourier coefficients of 1000 realizations, and then perform the inverse Fourier transform to obtain the real-space shear field imposing that the chosen Fourier modes satisfy the real number condition. Repeating this procedure, we made 1000 realizations of the Gaussian field. The simulated Gaussian fields generated in this way have the same power spectrum on average as that of the original simulations and contain Fourier modes over the same range of angular scales as in the original simulations.

A justification of the Gaussian fields is given in Figure 2, which shows the diagonal terms of power spectrum covariance matrix, measured from the original and Gaussian-simulated maps, as a function of multipoles. The simulation results are plotted relative to the expectation for a Gaussian field, where the Gaussian covariance is equal to the squared power spectrum.
The Gaussianized realization (blue histogram), respectively. The Gaussian simulation result is consistent with the Gaussian distribution that has zero mean and the same variance as that measured from the simulation. (A color version of this figure is available in the online journal.)

The simulation results (symbols) start to deviate from the Gaussian error expectations (short-dashed curve) computed from the first term of Equation (4). Note that we included only the Fourier modes confined within our simulations in the covariance calculation; we imposed \( P_{\delta}(k) = 0 \) at \( k < k_f \) as done in Figure 1. Contrary to the result in Figure 1, the Gaussian predictions with the \( k \)-cutoff effect appear to overestimate the simulation results on large separation angles, where the non-Gaussian errors are insignificant. On the other hand, the dotted curves show the results obtained from the Gaussian simulations we constructed (see Section 2.2), showing a good agreement with the simulation results on the large scales. Hence, we conclude that the analytical prediction given by Equation (4) is not sufficiently accurate over the scales we consider. In fact, as studied in detail in Appendix A, Equation (4) can be valid only when the survey area is sufficiently large, such as 1000 deg\(^2\). In Appendix A we develop an empirical model to compute the Gaussian covariance taking into account the finite survey-area effect. The long-dashed curve shows the modified analytical prediction for the Gaussian covariance, which is computed using Equation (A10) as well as including the \( k \)-cutoff for \( P_{\delta}(k) \). The figure clearly shows that the modified analytical prediction matches the Gaussian simulation results well. Thus, we need to properly account for both the finite range of Fourier modes and the finite survey-area effect in order to obtain an accurate prediction of the covariance at large separations.

The simulation results (symbols) start to deviate from the Gaussian simulation results on small separation angles due to the non-Gaussian error contribution. The plot shows that the non-Gaussian errors are more significant on smaller angles and for lower source redshifts, because of stronger nonlinear clustering.

3. RESULTS: CALIBRATING THE NON-GAUSSIAN COVARIANCES

3.1. Diagonal and Off-diagonal Components of the Covariance Matrix

In this section, we study the covariance matrix of shear correlation function using 1000 ray-tracing simulations. The symbols in Figure 4 show the diagonal components of the covariance matrix measured from 1000 simulations, for different source redshifts \( z_s = 0.6, 1.0, \) and \( 3.0 \), respectively. Again note that each simulation realization has an area of 25 deg\(^2\), so the plot shows the covariance expected when measuring the cosmic shear correlation from a survey with square-shaped survey geometry and 25 deg\(^2\). Here we ignored the intrinsic ellipticity noise (we will come back to this later). First of all, we should stress that, by using the 1000 realizations (25,000 deg\(^2\) in total), we can obtain well-converged measurements of the covariance elements over a range of the scales we consider. To be more quantitative, as shown in the appendix in Takahashi et al. (2011), covariances of the diagonal covariance elements scale approximately as \( (2/N_t)^{1/2} \), where \( N_t \) is the number of simulation realizations. Therefore, the covariance elements are measured to 4% level accuracies. We first compare the simulation results with the Gaussian error expectations (short-dashed curve) computed from the first term of Equation (4). Note that we included only the Fourier modes confined within our simulations in the covariance calculation; we imposed \( P_{\delta}(k) = 0 \) at \( k < k_f \) as done in Figure 1. Contrary to the result in Figure 1, the Gaussian predictions with the \( k \)-cutoff effect appear to overestimate the simulation results on large separation angles, where the non-Gaussian errors are insignificant. On the other hand, the dotted curves show the results obtained from the Gaussian simulations we constructed (see Section 2.2), showing a good agreement with the simulation results on the large scales. Hence, we conclude that the analytical prediction given by Equation (4) is not sufficiently accurate over the scales we consider. In fact, as studied in detail in Appendix A, Equation (4) can be valid only when the survey area is sufficiently large, such as 1000 deg\(^2\). In Appendix A we develop an empirical model to compute the Gaussian covariance taking into account the finite survey-area effect. The long-dashed curve shows the modified analytical prediction for the Gaussian covariance, which is computed using Equation (A10) as well as including the \( k \)-cutoff for \( P_{\delta}(k) \). The figure clearly shows that the modified analytical prediction matches the Gaussian simulation results well. Thus, we need to properly account for both the finite range of Fourier modes and the finite survey-area effect in order to obtain an accurate prediction of the covariance at large separations.

The simulation results (symbols) start to deviate from the Gaussian simulation results on small separation angles due to the non-Gaussian error contribution. The plot shows that the non-Gaussian errors are more significant on smaller angles and for lower source redshifts, because of stronger nonlinear clustering.
in structure formation at lower redshifts and on smaller length scales. For comparison, the solid curves show the halo model prediction developed in our previous paper (Sato et al. 2009). To be more precise, the halo model is used to compute the non-Gaussian covariance for the assumed cosmological model, including the “halo sampling variance term” (Sato et al. 2009) in addition to the non-Gaussian term (one-halo term). Then the solid curves are the sum of the halo-model-computed non-Gaussian covariance and the Gaussian covariance that is computed from the Gaussian simulations. The halo model predictions qualitatively well reproduce the simulation results on small separations as well as the source-redshift dependence. However, the halo model also shows a sizable disagreement due to the limitation.

Figure 5 shows the covariance matrices comparing the results for the original ray-tracing simulations, the Gaussian simulations, and the Gaussian prediction computed from the first term of Equation (4), where the \( k \)-cutoff and the finite survey-area effect are included. Note that all the results are for \( z_s = 1 \). The Gaussian prediction (right panel) and the Gaussian simulation results show a nice agreement for the scale dependences and amplitudes. The original simulation results show totally different scale dependences from the Gaussian results and display greater amplitudes at smaller separation angles (left lower corner) due to stronger non-Gaussian contributions.

Next we study the correlation coefficients to quantify strengths of the off-diagonal covariance components relative to the diagonal components:

\[
\rho[\xi_1(\theta), \xi_1(\theta')] = \frac{\text{Cov}[\xi_1(\theta), \xi_1(\theta')]}{\sqrt{\text{Cov}[\xi_1(\theta), \xi_1(\theta')]\text{[Cov[\xi_1(\theta'), \xi_1(\theta')]]}}}.
\]

The correlation coefficient is defined so that \( r = 1 \) for the diagonal components when \( \theta = \theta' \). For off-diagonal components when \( \theta \neq \theta' \), \( r \rightarrow 1 \) implies strong correlation between the two correlation functions of different angular scales, while \( r \rightarrow 0 \) means no correlation.

Figure 6 shows the correlation coefficients \( r[\xi_1(\theta), \xi_1(\theta')] \). There are significant correlations between different separation angles. Comparing the dotted and solid curves manifests less significant cross-correlations in the non-Gaussian errors than in the Gaussian errors, implying that the non-Gaussian errors preferentially contribute to the diagonal components.

### 3.2. A Fitting Formula of the Non-Gaussian Covariance Elements

By using the simulation results shown up to the preceding section, we derive a fitting formula to compute the non-Gaussian covariance as a function of separation angles and source redshifts. To do this we employ the method developed in Semboloni et al. (2007), which is to derive the calibration function that gives the non-Gaussian covariance contribution relative to the Gaussian covariance. Our results bring several improvements over the results in Semboloni et al. (2007). First, we use 1000 ray-tracing realizations for each source redshift (\( z_s = 0.6, 0.8, 1.0, 1.5, 2.0, 3.0 \)). Second, we carefully estimated the Gaussian covariance contribution using the Gaussian simulations (see Section 2.2), thereby enabling us to reliably estimate the relative contribution of the non-Gaussian covariance.

We define \( F(\theta, \theta'; z_s) \), the ratio of the non-Gaussian covariance relative to the Gaussian expectation for the covariance.
1000 Gaussian simulations as in Figure 2. the 1000 realizations where the Gaussian contributions are estimated from the matrix:

\[ F(\theta, \theta'; z_s) = \frac{\text{Cov}_{NG}[\xi_s(\theta), \xi_s(\theta'); z_s]}{\text{Cov}_{GL}[\xi_s(\theta), \xi_s(\theta'); z_s]} \].

Here we used the 1000 simulations to compute the Gaussian and non-Gaussian covariance matrices appearing in the numerator and denominator of the above equation. As shown in Figures 4 and 5, the non-Gaussian contributions are important only on small separation angles, \(<10 \text{ arcmin}, for a \Lambda CDM cosmology and for source redshifts we consider.

Figure 7 shows the simulation results for the diagonal components of \(F(\theta, \theta')\) for different source redshifts. The fitting formula for \(F(\theta, \theta')\) is given in Appendix B. The figure shows that all the curves go to unity, \(F(\theta, \theta) = 1\), on very large separations as expected; the non-Gaussian covariances become negligible on such large separations. This can be contrasted to the results in Semboloni et al. (2007), see Figure 1 in their paper), where the corresponding curves do not go to unity, even go below unity at large separations. This is because we carefully computed the Gaussian covariance contribution (see Section 2.2), while Semboloni et al. (2007) used the analytical prediction (the first term of Equation (4)) to estimate the Gaussian covariance, which turns out to overestimate the simulation results. Also note that in Semboloni et al. (2007) all the Fourier modes setting the lower bound to \(k = 0\) or \(l = 0\) are included in the Gaussian covariance calculation (Equation (4)).

The figure also shows that the non-Gaussian errors are significant on smaller separations and for lower source redshifts, where nonlinear clustering is more evolving. For a source redshift \(z_s \sim 1\), which is a typical depth of the Subaru-type survey, \(F \gtrsim 10\) on scales smaller than 1 arcmin, meaning that the non-Gaussian contribution to the diagonal covariance is greater than the Gaussian contribution by more than a factor of 10. The non-Gaussian covariance amplitudes are by accident similar to what is found in Semboloni et al. (2007), even though the power spectrum normalization \(\sigma_8\) is quite different: \(\sigma_8 = 0.76\) in our simulations, while \(\sigma_8 = 1\) in Semboloni et al. (2007). Again this is subscribed to the fact that Semboloni et al. (2007) underestimated the non-Gaussian error contribution. The normalization \(\sigma_8 = 0.76\) we assumed is slightly lower than the currently most-favored value, \(\sigma_8 = 0.8\) (see WMAP seven-year results; Komatsu et al. 2011). Therefore, the fitting function \(F(\theta, \theta')\) we calibrated may slightly underestimate the non-Gaussian errors (by about 20%). To correct this, we can use the halo model prediction to estimate the difference in the non-Gaussian covariance amplitudes for different \(\sigma_8\) values and then multiply the correction factor with \(F(\theta, \theta')\).

Let us summarize how to obtain the covariance matrix for given survey parameters from our fitting formula.

1. Compute the first term of Equation (A10) to estimate the Gaussian covariance matrix, for a given survey area and source redshift.
2. Use the fitting function Equation (B1) for \(F(\theta, \theta'; z_s)\) to obtain the non-Gaussian covariance contribution.
3. Multiply the quantities in steps 1 and 2 to obtain the total covariance matrix.

Exactly speaking, the survey-area dependence of the non-Gaussian covariance is not as naively expected; \(\text{Cov} \propto 1/\Omega_s\) does not hold due to the halo sampling variance contribution (Sato et al. 2009). However, we have found that the residual dependence is relatively small, and our fitting formula for the covariance matrix is approximately valid for the survey area we are most interested in (\(\gtrsim 100 \text{ deg}^2\)).

While we have so far ignored the intrinsic ellipticity contribution to the covariance, we need to further include the effect. First of all, the intrinsic ellipticity noise contributes only to the Gaussian covariance, and does not affect the non-Gaussian covariance, as long as the intrinsic ellipticity alignment can be ignored. Hence we can easily include the shot noise contribution as follows.

One method is a simulation-based method. We can generate the Gaussian field including the shot noise contribution by replacing the power spectrum \(P_\kappa(l)\) with \(P_\kappa(l) + \sigma_n^2/\bar{n}_g\) in generating the simulation field, where \(\sigma_n\) is the rms intrinsic ellipticity per component and \(\bar{n}_g\) is the mean number density of source galaxies. Here we need to assume \(\sigma_n\) and \(\bar{n}_g\) that we measure from galaxies in a given survey. If we measure the covariance matrix from the Gaussian simulations generated in this way, the covariance matrix includes the contribution arising from the term \(\propto (\sigma_n^2/\bar{n}_g)^2\) as well as the mixed term between the cosmological Gaussian field and the shot noise term arising from the term \(\propto P_\kappa(l)\). (Schneider et al. 2002; Joachimi et al. 2008).

Another way is by following the method in Joachimi et al. (2008; also see Schneider et al. 2002), who developed an analytical formula of the Gaussian covariances including the intrinsic ellipticity noise contribution. To be more explicit, the formula is given in terms of the convergence power spectrum \(P_\kappa(l)\), as in the first term of Equation (4). Then the intrinsic noise contribution can be incorporated by replacing \(P_\kappa(l)\) with \((P_\kappa(l) + \sigma_n^2/\bar{n}_g)^2\). Here we need to assume \(\sigma_n\) and \(\bar{n}_g\) that are measured from a given survey.

Finally we comment on other contributions to the covariance matrix we have so far ignored, which are the covariance contributions arising from another shear correlation function \(\xi_-(\theta, \xi_-(\theta'))\) and Cov\[[\xi_-(\theta), \xi_-(\theta')]\] and Cov\[[\xi_+(\theta), \xi_+(\theta')]\] (Figure 8 shows the results). Again the non-Gaussian error contributions are significant at scales \(<10\) '. Compared to Figure 4, the covariance matrices Cov\[[\xi_-(\theta), \xi_-(\theta')]\] and Cov\[[\xi_+(\theta), \xi_+(\theta')]\] have smaller amplitudes than Cov\[[\xi_+(\theta), \xi_+(\theta')]\] does: for example, the amplitudes of Cov\[[\xi_-(\theta), \xi_-(\theta')]\] are smaller.
ical predictions computed from Equations (30) or (31) in Joachimi et al. (2008), the Gaussian simulations (see Section 2.2), while the dashed curves the theoretical predictions computed from Equations (30) or (31) in Joachimi et al. (2008), we included the k-cutoff in the lensing power spectrum calculation.

(A color version of this figure is available in the online journal.)

than that of \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) by a factor of 100 and 10, respectively. However, the genuine effects need to be understood in terms of the signal-to-noise ratios that are roughly estimated as \( \xi^2 / \text{Cov}[\xi_i, \xi_i] \) or \( \xi / \text{Cov}[\xi_i, \xi_j] \) at each separation angle. Since the correlation function \( \xi \) has smaller amplitudes than \( \xi \), does, by a factor of 10 at separations \( \sim 1' \) (e.g., see Figure 2 in Schneider et al. 2002), therefore the covariances \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) and \( \text{Cov}[\xi_i(\theta), \xi_j(\theta') \) are not negligible.

We tried to derive fitting formulas for the non-Gaussian covariance contributions to \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) and \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) in a similar manner as done in Equation (6). However, due to complex scale dependences of the Gaussian covariances as implied in Figure 8, we could not find useful fitting formulas as expressed by simple analytical functions. Therefore, the covariance matrix contributions need to be directly calibrated from the ray-tracing simulations. The table-format covariances for \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) and \( \text{Cov}[\xi_i(\theta), \xi_j(\theta')] \) are available upon request.

4. CONCLUSION

In this paper, we have developed the theoretical model of the covariance matrix of cosmic shear two-point correlation function taking into account the effect of finite survey area and the effects of nonlinear gravitational clustering in large-scale structure.

We found that the survey-area dependence of the Gaussian covariance, which scales as \( \propto 1/\Omega \), in the commonly used formula, does not hold for a small-area survey due to the effect of finite survey area. The conventional formula is valid only when the survey area is sufficiently wide, such as 1000 deg\(^2\). We examined the residual survey-area dependence using the method developed by Schneider et al. (2002), and obtained an empirical formula which reproduces our results.

We examined the non-Gaussian covariance as a function of angular scales and source redshifts by using two sets of simulation data: (1) the ray-tracing simulations for the standard \( \Lambda \)CDM cosmology and (2) Gaussian fields which have the same power spectrum on average as that of the original simulations. The non-Gaussian errors become more significant on smaller scales and at lower redshifts. We compared the simulation results with halo model predictions and found that the halo model qualitatively well reproduces the non-Gaussian error over a wider range of separation angles and for redshifts we have considered. However, the halo model also displays sizable disagreement with the simulation results.

Following Semboloni et al. (2007), we derived the calibration function to compute the non-Gaussian covariance contribution relative to the Gaussian covariance (Equation (6)). The Gaussian field data allows us to cleanly separate out the Gaussian covariance contribution accurately, thereby enabling us to reliably estimate the calibration function. We found that the calibration factor at arcminute scales can be high as \( \sim 20 \) and \( \sim 10 \) for source redshifts of \( z_s = 0.6 \) and 1.0, respectively. The transition between Gaussian and non-Gaussian covariance occurs around 10 and 5 arcmin for \( z_s = 0.6 \) and 1.0, respectively. Therefore, when one derives constraints on the cosmological parameters from cosmic shear correlation measurements, it is important to properly account for the non-Gaussian effects. The fitting formula, Equation (A10) and Equation (B1), developed in this paper allow one to compute the covariance matrix including the non-Gaussian contribution for given survey parameters (the survey area and the source redshift).

Simulation data (1000 convergence power spectra and cosmic shear correlation functions for \( \xi_i(\theta) \) and \( \xi_j(\theta') \)) are available upon request (contact masanori@a.phys.nagoya-u.ac.jp).

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APPENDIX A

FINITE-AREA EFFECT OF THE GAUSSIAN COVARIANCE

In this section, we study the validity of the first term of Equation (4), which gives the Gaussian error prediction for the shear correlation function covariance, and we will show the prediction is only valid for a large-area survey covering more than 1000 deg\(^2\). For this purpose we will use the method developed in Schneider et al. (2002).
Let us begin by considering an estimator of the shear correlation function of separation angle \( \theta \), \( \hat{\xi}_s(\theta) \). For a given galaxy catalog the shear correlation function can be estimated as

\[
\hat{\xi}_s(\theta) = \frac{1}{N_{\text{pair}}} \sum_i \sum_j \left( \epsilon_{\theta(i)} \epsilon_{\theta(j)} + \epsilon_{\phi(i)} \epsilon_{\phi(j)} \right) \Delta(|\theta_i - \theta_j|; \theta), \tag{A1}
\]

where we have used the abbreviated notations such as \( \epsilon_{\theta(i)} \) to denote the ellipticity component of the \( i \)th galaxy at angular position \( \theta_i \), \( N_{\text{pair}} \) is the total number of pairs of galaxies that are separated by separation angle \( \theta \) and index \( i \) in summation runs over all the galaxies in the catalog. The tangential and cross components of the ellipticity \( \epsilon = \epsilon_1 + i \epsilon_2 \) at position \( \theta \) are defined as

\[
\epsilon_1 = -Re(\epsilon e^{-2i\phi}); \quad \epsilon_2 = -Im(\epsilon e^{-2i\phi}), \tag{A2}
\]

where \( Re \) and \( Im \) denote the real and imaginary parts of the quantities and \( \phi \) is the polar angle of the separation vector between two galaxies, \( \theta \). The component, \( \epsilon_1 \), is defined as the ellipticity component in a parallel or perpendicular direction relative to the line connecting the two galaxies. On the other hand \( \epsilon_2 \) are measured from the \( \pm 45^\circ \) rotated components. The function \( \Delta(|\theta_i - \theta_j|; \theta) \) is a selection function defined such that \( \Delta(|\theta_i - \theta_j|; \theta) = 1 \) if \( \theta - \theta / 2 \leq |\theta_i - \theta_m| \leq \theta + \theta / 2 \), otherwise \( \Delta(|\theta_i - \theta_j|; \theta) = 0 \), where \( \delta \theta \) is the bin width of the separation angle. The total number of galaxy pairs is given as \( N_{\text{pair}} = \sum_{ij} \Delta(|\theta_i - \theta_j|; \theta) \). The ensemble average of the estimator Equation (A1) is found to indeed give the shear correlation function:

\[
\langle \hat{\xi}_s(\theta) \rangle = \frac{1}{N_{\text{pair}}} \sum_{ij} \left( \epsilon_{\theta(i)} \epsilon_{\theta(j)} + \epsilon_{\phi(i)} \epsilon_{\phi(j)} \right) \Delta(|\theta_i - \theta_j|; \theta) = \frac{1}{N_{\text{pair}}} \sum_{ij} \hat{\xi}_s(|\theta_i - \theta_j|) \Delta(|\theta_i - \theta_j|; \theta) = \xi_s(\theta). \tag{A3}
\]

Similarly, the covariance is defined in terms of the estimator \( \hat{\xi}_s(\theta) \) as

\[
\text{Cov}[\xi_s(\theta), \xi_s(\theta')] = (\hat{\xi}_s(\theta) \hat{\xi}_s(\theta')) - \xi_s(\theta) \xi_s(\theta'). \tag{A4}
\]

For simplicity, let us consider the diagonal parts of the covariance matrix, \( \theta = \theta' \). For the Gaussian field, the diagonal parts are computed as (Schneider et al. 2002)

\[
\text{Cov}[\xi_s(\theta), \xi_s(\theta)] = \frac{1}{N_{\text{pair}}} \sum_{ijlm} \left( \epsilon_{\theta(i)} \epsilon_{\theta(l)} + \epsilon_{\phi(i)} \epsilon_{\phi(l)} \right) \Delta(|\theta_i - \theta_j|; \theta) \Delta(|\theta_l - \theta_m|; \theta - \xi_s(\theta))^2
\]

\[
= \frac{1}{N_{\text{pair}}} \sum_{ijlm} \left[ \xi_s(|\theta_i - \theta_m|) \xi_s(|\theta_j - \theta_l|) + \cos[\Delta(\psi_{lm} - \psi_{ij})] \xi_s(|\theta_i - \theta_m|) \xi_s(|\theta_j - \theta_l|) \right] \Delta(|\theta_i - \theta_j|; \theta) \Delta(|\theta_l - \theta_m|; \theta)
\]

\[
= \frac{1}{N_{\text{pair}}} \sum_{ijlm} F_{ijlm}, \tag{A5}
\]

where \( \psi_{lm} \) is the polar angle of the difference vector \( \theta_i - \theta_m \), and we used the fact that an estimator for \( \xi_\theta(\theta) \) is analogously defined as

\[
\hat{\xi}_\theta(\theta) = \frac{1}{N_{\text{pair}}} \sum_i \sum_j \left( \epsilon_{\theta(i)} \epsilon_{\theta(j)} + \epsilon_{\phi(i)} \epsilon_{\phi(j)} \right) \Delta(|\theta_i - \theta_j|; \theta). \tag{A6}
\]

Now we use Equation (A5) to study the effect of finite survey area. This can be done by comparing the result with the first term of Equation (4) because Equation (4) ignores the survey geometry effect. To do this we performed the simplified test. First, we randomly distribute galaxy positions with square shape geometry. Then, rather than working on the shear field in simulations, we will compute the summation in Equation (A5) by using the tabulated data of \( \xi_s(\theta) \) and \( \xi_\theta(\theta) \). We estimate \( \xi_s(\theta) \) and \( \xi_\theta(\theta) \) using Equations (1) and (2). In this case, the summation such as \( \sum_{ij} \) runs over all the galaxies in the square-shaped mock simulation, and the separation angle such as \( |\theta_i - \theta_j| \) can be exactly computed from the separation between the two chosen galaxies.
Figure A1. Numerical test for studying the finite-area effect on the Gaussian covariance of shear correlation (see the text for the details). The symbols show the results for the diagonal covariance elements, which are computed using Equation (A5), for different areas of the square-shaped mock simulations: $\Omega_s = 1.5625 \, \text{deg}^2$, $25 \, \text{deg}^2$, and $3200 \, \text{deg}^2$. The source redshift is $z_s = 1.0$. The solid curves are the prediction computed from the first term of Equation (4). The two results agree for a large area such as $\Omega_s = 3200 \, \text{deg}^2$, but disagree for the smaller areas probably due to the finite-area effect.

(The color version of this figure is available in the online journal.)

The symbols in Figure A1 show the results of Equation (A5) for the diagonal covariance matrix elements as a function of separation angles and mock simulation areas. The solid curves are the results computed from the first term of Equation (4). In both cases we used the HaloFit prediction to compute the lensing power spectrum, which is then used to compute the shear correlation function as well as to compute the first term of Equation (4). Note that we do not plot the symbols where separation angle becomes comparable with the scale of the mock simulation area in order to avoid the boundary effect of the square-shaped mock simulation.

The figure clearly shows that the symbol is in good agreement with the solid curve for the largest area we consider, $\Omega_s = 3200 \, \text{deg}^2$, however, the two results disagree in amplitudes for the smaller areas, although the shape looks similar. In addition, comparing the results for $\Omega_s = 1.56$ and $25 \, \text{deg}^2$ manifests that the disagreement is greater for the smaller survey area. This disagreement arises due to the effect of the finite survey area. Hence the conventionally used expression for the Gaussian covariance, the first term of Equation (4), appears to overestimate the covariance amplitude. The formula is only valid for a sufficiently large area such as $\Omega_s \gtrsim 1000 \, \text{deg}^2$. In other words, due to the finite survey-area effect, the covariance of shear correlation function does not scale with survey area as $\text{Cov} \propto 1/\Omega_s$, which is assumed in the conventional formula (Equation (4)).

Hereafter, we will study in more detail how the difference between the results of Equations (4) and (A5) arises. Let us consider two survey areas A and B, assuming area B is included in area A ($A \supset B$). By using Equation (A5), the diagonal covariance matrix for survey A can be expressed as

$$
\text{Cov}_A[\xi_+(\theta), \xi_+(\theta)] = \frac{1}{N_{\text{pair}}^2} \sum_{ij \in A} \sum_{lm \in A} F_{ijlm} + 4 \sum_{i \in B} \sum_{jlm \in A - B} F_{ijlm} + 2 \sum_{ij \in B} \sum_{lm \in A - B} F_{ijlm}
+ 2 \sum_{il \in B} \sum_{jm \in A - B} F_{ijlm} + 2 \sum_{im \in B} \sum_{jl \in A - B} F_{ijlm} + 4 \sum_{ijl \in B} \sum_{m \in A - B} F_{ijlm} + \sum_{ijlm \in B} F_{ijlm},
$$

(A7)

where the notation $ij \in B$ is introduced to mean that the indices $i$ and $j$ are included in B, and the notation $lm \in A - B$ means that the indices $l$ and $m$ are included in the region that is in $A$, but not in B. We will consider the case that survey area A is sufficiently large in the following discussion. We define the value arising from finite-area effect as

$$
\text{FAE} \equiv \frac{A}{B} \left( \text{Cov}_A[\xi_+(\theta), \xi_+(\theta)] - \text{Cov}_B[\xi_+(\theta), \xi_+(\theta)] \right).
$$

(A8)

If B is close to A, there is no finite-area effect and FAE should be zero because of the survey area as $\text{Cov} \propto 1/\Omega_s$. Also, in this case, the final term of Equation (A7) has a dominant contribution because the number of galaxy pairs is greater than the other terms.
Figure A2. Fitting formula for the survey-area dependence of the Gaussian covariance, $f(\Omega_s)$ in Equation (A10). The symbols are the mock simulation results for different source redshifts as in Figure A1, and the solid curves are the fitting formula given by Equation (A11). We did the fitting by matching to the mock simulation results for the diagonal Gaussian matrix at the scale of 50 arcmin.

(A color version of this figure is available in the online journal.)

In this case, Equation (A8) becomes

$$FAE \equiv \frac{A}{B} \text{Cov}_A[\xi_s(\theta), \xi_s(\theta)] - \text{Cov}_B[\xi_s(\theta), \xi_s(\theta)] \simeq \frac{A}{B} \frac{1}{N_{\text{pair}}^2} \sum_{ijlm \in A} \sum_{ijlm \in B} F_{ijlm} - \text{Cov}_B[\xi_s(\theta), \xi_s(\theta)] \simeq 1 \frac{N_{\text{pair}}^2}{|ijlm \in B|} \sum_{ijlm \in B} F_{ijlm} - \text{Cov}_B[\xi_s(\theta), \xi_s(\theta)] - 0.$$  

(A9)

Thus, Equation (A8) has an asymptotic limit of $\text{Cov}_A = \text{Cov}_B$ when $A = B$. However, the other terms in Equation (A7) are not negligible if $A \neq B$, and the covariances for a general case do not scale with the survey area as $\text{Cov} \propto 1/\Omega_s$, due to a finite survey-area effect.

Therefore, we will estimate a fitting formula to account for the survey-area dependence by assuming the form

$$\text{Cov}[\xi_s(\theta), \xi_s(\theta')]} = \frac{1}{\pi \Omega_s f(\Omega_s)} \int_0^\infty ldl' J_0(l\theta) J_0(l'\theta') P_c(l)^2 + \frac{1}{4\pi^2 \Omega_s f(\Omega_s)} \int_0^\infty ldl' \int_0^\infty l'dl'' l'J_0(l\theta)J_0(l''\theta')\overline{T}_c(l,l'),$$  

(A10)

where $f(\Omega_s)$ denotes the new survey-area dependence. We parameterize $f(\Omega_s)$ as

$$f(\Omega_s) = \frac{\alpha(z_s)}{\Omega_s^{\beta(z_s)}},$$  

(A11)

We estimate the two parameters using the mock simulations as in Figure A1, for different source redshifts $z_s = 0.6, 0.8, 1.0, 1.5, 2.0,$ and 3.0. The mock simulation results are fitted well by the parameters

$$\alpha(z_s) = \alpha_1 z_s^{\alpha_2}$$  

$$\beta(z_s) = \beta_1 z_s^{\beta_2}.$$  

(A12)

The best-fitting parameters are found to be $(\alpha_1, \alpha_2) = (3.2952, -0.316369)$ and $(\beta_1, \beta_2) = (0.170708, -0.349913)$, respectively. As shown in Figure A2, we performed the fitting over survey areas of $1.5625 \text{ deg}^2 \leq \Omega_s \leq 1600 \text{ deg}^2$ using the diagonal covariance at 50 arcmin. However, we checked that the above fitting formula reproduces fairly well the results for different separations and for the off-diagonal covariance elements. A cautionary note regarding the use of the fitting formula is that the output value should be replaced to unity if the value is below unity.

APPENDIX B

FITTING FORMULA FOR CALIBRATION MATRIX

In this section we estimate the calibration function $F(\theta, \theta'; z_s)$ we studied in Section 3.2, which can be used to estimate the non-Gaussian covariance in combination with the fitting formula (A10) for the Gaussian covariance. We parameterize
Figure B1. Diagonal components of the calibration function to compute the non-Gaussian covariance, \( F(\theta, \theta; z_s) \) (see Equation (6) for the definition). The symbols are the same as in Figure 7, and the solid curves are the fitting formula given by Equation (B1).

(A color version of this figure is available in the online journal.)

\[
F(\theta, \theta; z_s) = a(z_s) + b(z_s) \cdot d(z_s)^{|\theta - \theta'|}. 
\]

The four parameters are estimated from the ray-tracing simulations for six different source redshifts \( z_s = 0.6, 0.8, 1.0, 1.5, 2.0, \) and 3.0. As demonstrated in Figures B1 and B2, the simulation results are fitted well by the following best-fitting parameters:

\[
\begin{align*}
   a(z_s) &= -z_s^{a_1} \exp(a_2 z_s) + a_3 \\
   b(z_s) &= b_1 z_s^{b_1} + b_3 \\
   c(z_s) &= c_1 z_s^{c_2} + c_3 \\
   d(z_s) &= d_1 z_s^{d_2} + d_3,
\end{align*}
\]

where \((a_1, a_2, a_3) = (-3.7683, 0.9752, 1.4048), (b_1, b_2, b_3) = (10.7926, -2.0284, -0.2266), (c_1, c_2, c_3) = (-0.3664, -0.5733, 0.6863),\) and \((d_1, d_2, d_3) = (0.2450, 0.1218, 0.7076),\) respectively. We performed this fitting over angular scales \(0.5 \text{ arcmin} \leq \{\theta, \theta'\} \leq 10 \text{ arcmin}.\) Figures B1 and B2 clearly show that the fitting formula above reproduces the simulation results well, and the accuracy of the fitting formula is within about 25%. However, it should be noted that the fitting formula is only applied to source redshift ranges \(0.6 \leq z_s \leq 3.0\) and angular scales below 10 arcmin. This is sufficient because the non-Gaussian covariance is important only below 10 arcmin.

Figure B2. Same as Figure B1, but for the off-diagonal components. Shown is the function \( F(\theta, \theta') \) as a function of \( \theta, \) but \( \theta' \) is kept fixed to \( \theta' = 0.794, 2.51, \) and 7.94 (arcmin) in the left, middle, and right panels, respectively.

(A color version of this figure is available in the online journal.)
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