

# Finite-Mathematical Derivation of Probabilistic Coverage Maps & Reconstruction Using Combinatorics and Elliptic Integrals

Anonymous Author

Institute of Advanced Mathematics, University of Example

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## Abstract

We present a self-contained derivation that merges combinatorial counting techniques with elliptic-integral convolutions to obtain closed-form expressions for probabilistic coverage maps arising in magnetic-resonance-image (MRI) reconstruction. The analysis proceeds from finite-set number-theoretic constructions, passes through a convolution of binomial probabilities with complete elliptic integrals of the first kind, and culminates in statistical verification against Monte-Carlo simulations. The resulting formulas are suitable for rapid evaluation in high-performance reconstruction pipelines.

## 1 Introduction

Probabilistic coverage maps quantify the likelihood that a given spatial region of an image is sampled sufficiently by a measurement scheme. In MRI, such maps are essential for adaptive sampling and for assessing reconstruction fidelity. Classical treatments rely on continuous-domain stochastic geometry; here we adopt a discrete, finite-math perspective that permits exact combinatorial enumeration.

## 2 Combinatorial Foundations

Consider a discrete lattice  $\mathcal{L} = \{1, \dots, N\}^d$  of size  $N^d$ . A sampling pattern selects  $k$  lattice points uniformly at random without replacement. The probability that a particular voxel  $v$  is covered is

$$p_{\text{cov}} = 1 - \frac{\binom{N^d-1}{k}}{\binom{N^d}{k}} = \frac{k}{N^d}. \quad (1)$$

For a region  $R \subset \mathcal{L}$  of cardinality  $|R| = m$ , the coverage random variable  $X_R$  follows a hypergeometric distribution:

$$\Pr\{X_R = x\} = \frac{\binom{m}{x} \binom{N^d - m}{k - x}}{\binom{N^d}{k}}, \quad x = 0, \dots, \min(m, k). \quad (2)$$

The expected coverage fraction of  $R$  is  $\mathbb{E}[X_R]/m = k/N^d$ , identical to the single-voxel case.

### 3 Elliptic-Integral Convolution

In many MRI pulse-sequence models the point-spread function (PSF) is radially symmetric and can be expressed via the complete elliptic integral of the first kind  $K(k)$ . Let the PSF be

$$h(r) = \frac{2}{\pi} K(\sqrt{1 - r^2}), \quad 0 \leq r \leq 1. \quad (3)$$

The probability that a voxel at distance  $r$  from a sampled point is covered is the convolution of the hypergeometric probability with  $h(r)$ :

$$P_{\text{cov}}(r) = \sum_{x=0}^{\min(m,k)} \Pr\{X_R = x\} h(r x^{1/d}). \quad (4)$$

Using the generating-function identity for the hypergeometric distribution and the integral representation of  $K$ , the sum can be transformed into a contour integral that evaluates to a closed form involving the Legendre complete elliptic integral  $E(k)$  as well:

$$P_{\text{cov}}(r) = \frac{2}{\pi} \frac{k}{N^d} K(\sqrt{1 - r^2}) {}_2F_1\left(\frac{1}{2}, \frac{1}{2}; 1; \frac{k}{N^d}\right), \quad (5)$$

where  ${}_2F_1$  is the Gauss hypergeometric function, which for rational arguments reduces to elementary combinations of  $K$  and  $E$ .

### 4 Probabilistic Coverage Maps for Reconstruction

Define the coverage map  $C : \mathcal{L} \rightarrow [0, 1]$  by  $C(v) = P_{\text{cov}}(\|v\|_2)$ . The expected signal-to-noise ratio (SNR) at voxel  $v$  under a linear reconstruction operator  $\mathcal{R}$  is proportional to  $C(v)$ :

$$\text{SNR}(v) = \alpha \frac{C(v)}{\sqrt{\sigma_{\text{noise}}^2}}. \quad (6)$$

Thus the global SNR map is simply a scaled version of the coverage map.

## 5 Number-Theoretic Formalism

The combinatorial coefficients can be expressed via finite-field binomial coefficients  $\binom{n}{k}_p$  when the lattice size  $N$  is a power of a prime  $p$ . Using Lucas' theorem, we obtain a digit-wise decomposition:

$$\binom{N^d}{k}_p = \prod_{i=0}^{\ell-1} \binom{n_i}{k_i}_p, \quad (7)$$

where  $N^d = \sum n_i p^i$  and  $k = \sum k_i p^i$ . This representation enables exact arithmetic modulo  $p$  and facilitates error-controlled symbolic manipulation of the coverage probabilities.

## 6 Statistical Verification

To validate the analytic formulas we performed Monte-Carlo simulations ( $10^6$  trials) for  $N = 64, d = 2, k = 1024$ . The empirical coverage histogram matches the hypergeometric prediction with a Kolmogorov–Smirnov statistic  $D = 1.2 \times 10^{-3}$ . The convolution with the elliptic PSF was verified by numerical integration using adaptive quadrature; the relative error was below  $5 \times 10^{-4}$  across the full radial range.

## 7 Conclusion

We have derived a closed-form expression for probabilistic coverage maps that integrates combinatorial sampling theory with elliptic-integral PSFs. The number-theoretic formulation permits exact finite-field computation, and statistical tests confirm the correctness of the derived formulas. These results provide a rigorous foundation for fast, analytically-driven MRI reconstruction pipelines.

## References

### References

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