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Monte Carlo Method for Estimating the Area of Irregular Shapes

Zhixuan Li

Changjun Bilingual School, Changsha, China
1540968604@qq.com

Abstract. In daily life, there is a practical demand for area estimation of irregular graphics in scenarios such as leaf area measurement, map jurisdiction area calculation, and art design graphic area estimation. Among traditional estimation methods, the grid method is cumbersome to operate, the formula method is only applicable to regular graphics, and instrument measurement has high costs, which makes it difficult to meet the low-cost and easy-to-operate estimation needs. This study aims to verify the feasibility of the Monte Carlo method in estimating the area of irregular graphics and analyze the key factors affecting the estimation accuracy. This study combines manual simulation and Python programming simulation, uses the control variable method to compare the estimation results under different experimental conditions, and selects three typical irregular graphics: sycamore leaves, hand-drawn cartoon avatars, and the map jurisdiction of Yuelu District, Changsha City for experiments. The results show that the Monte Carlo method is suitable for area estimation of any irregular graphics, the estimation accuracy improves with the increase of the number of points, the error can be controlled within 2% when 10,000 points are cast, and the programming simulation accuracy is significantly higher than manual simulation, with the error rate 3%-5% lower than manual simulation. This study provides a simple and feasible area estimation scheme for irregular graphics for high school students, realizes the combination of probability knowledge and practical application, and provides an interdisciplinary (mathematics + programming) practical case.

Keywords: Monte Carlo method, area estimation of irregular shapes, controlled variable method, programming simulation, accuracy analysis

1. Introduction

Scenarios such as measuring the area of leaves, calculating the area of map regions, estimating the area of artistic designs, and estimating the area of irregular farmland all involve estimating the area of irregular shapes. These shapes are difficult to calculate directly using traditional formulas. Traditional estimation methods include the grid method, which is cumbersome, requiring counting each square individually; it is time-consuming and is prone to human error; the formula method, which is only suitable for regular shapes with specific patterns, cannot adapt to irregular shapes with complex edges; and the instrument measurement method, which is costly and difficult to popularize in secondary school practical scenarios.

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The core of the Monte Carlo method is solving mathematical problems through random sampling [1]. Its key element, "random simulation", requires no complex mathematical formulas, making it easy to implement and suitable for practice within the knowledge range of high school students. It can effectively solve the challenge of estimating the area of irregular shapes. Through manual simulation and simple programming simulation, the feasibility of this method in a middle school practical scenario is verified, ensuring that students can complete the experiment using their existing probability knowledge and basic programming skills.

Through controlled variable experiments, the degree of influence of different factors on estimation accuracy is clarified, providing optimization directions for the practical application of the method. This research is conducted in four stages: theoretical learning stage, learning the basic principles of the Monte Carlo method and related knowledge of geometric probability; experimental design stage, determining the experimental subjects, experimental scheme, and variable control rules; result analysis stage, comparing the experimental results of manual simulation and programming simulation, and analyzing the sources of error and factors affecting accuracy; method optimization stage, proposing optimization strategies and verifying the optimization effect.

This paper is divided into 7 chapters: Chapter 1 is the introduction, introducing the research background, purpose, and framework; Chapter 2 is the relevant theoretical foundation, explaining the principles and characteristics of the Monte Carlo method; Chapter 3 is the experimental design and preparation, explaining the experimental subjects, scheme, and variable control; Chapter 4 is the experimental process and result analysis, presenting experimental data and error analysis; Chapter 5 is the method optimization and improvement, proposing optimization strategies and verifying their effects; Chapter 6 is the application expansion and practical significance, explaining the practical application scenarios of the method; Chapter 7 is the conclusion, summarizing the research results and shortcomings.

2. Relevant theoretical foundations

2.1. Basic principles of the Monte Carlo method

2.1.1. Origin and definition of the Monte Carlo method

The Monte Carlo method, named after the Monaco casino, is fundamentally about solving mathematical problems through random sampling [1]. It combines stochastic processes with mathematical calculations, making it suitable for complex problems that are difficult to solve analytically.

2.1.2. Geometric probability principle for estimating area

Using Random Point Rolling let the area of the irregular shape be S_1, the area of the region surrounding the shape be S_2, the total number of randomly rolled points be N, and the number of points falling within the shape be n. According to the geometric probability principle, the area of the irregular shape can be estimated as:

$$\widehat{S}_1 = S_2 \times \frac{n}{N} \tag{1}$$

The theoretical justification follows directly from the law of large numbers: as $N \to \infty$, the sample proportion n/N converges in probability to the true area ratio S_1/S_2 [2]. The standard error of

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the estimate scales as $1/\sqrt{N}$ [3], implying that a hundredfold increase in the number of points reduces the error by approximately one order of magnitude.

2.1.3. Mathematical derivation of the estimation error

To understand the theoretical limits of estimation accuracy, the statistical properties of the estimator in Equation (1) can be derived. Let $p = S_1/S_2$ denote the true probability that a uniformly random point in the bounding rectangle falls inside the irregular shape. The random variable n—the number of points falling within the shape out of N independent trials—follows a binomial distribution with parameters N and p, that is, $n \sim B(N, p)$ [4]. The estimator for the shape area is:

$$\widehat{S}_1 = S_2 \times \frac{n}{N}$$

The expected value and variance of this estimator are:

$$E\left[\widehat{S}_1\right] = S_2 \times \frac{E[n]}{N} = S_2 \times \frac{Np}{N} = S_2 p = S_1 \tag{2}$$

$$Var\left[\widehat{S}_1\right] = S_2^2 \times \frac{Var[n]}{N^2} = S_2^2 \times \frac{Np(1-p)}{N^2} = \frac{S_2^2 p(1-p)}{N} \tag{3}$$

Equation (2) confirms that the estimator is unbiased: the expected value of the estimate equals the true area S_1 regardless of the sample size N. Equation (3) reveals that the variance of the estimate decreases inversely with N, meaning that the standard deviation scales as $1/\sqrt{N}$ [5]. From this, the absolute percentage error can be approximated as:

$$\varepsilon \approx \frac{S_2\sqrt{p(1-p)}}{\sqrt{N} \times S_1} \times 100\% \tag{4}$$

This derivation provides the theoretical foundation for the experimental design in this study. Specifically, Equation (4) predicts that if a relatively coarse estimate at N=100 yields an error of approximately 10%, then increasing to N = 10,000 (a hundredfold increase) should reduce the error to approximately 1%. This prediction can be directly tested against the experimental results. The derivation also reveals that the factor $p(1-p)$—which reaches its maximum at p=0.5—determines the intrinsic difficulty of estimating a given shape: shapes whose area occupies roughly half of the enclosing rectangle are theoretically the most challenging to estimate accurately.

2.2. Characteristics of the Monte Carlo method

2.2.1. Advantages

It requires no complex mathematical formulas, is applicable to irregular shapes of any form [3], has a low implementation threshold, and can be implemented through manual simulation or simple programming.

2.2.2. Disadvantages

The results are random; the estimation accuracy depends on the number of rolls [3], and there is a certain systematic error. Repeated experiments are needed to reduce random errors.

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2.3. Computational logic of the point-in-polygon test

A critical computational step in the programming simulation is determining whether a randomly generated point lies inside or outside the irregular shape. This section presents the ray-casting algorithm, which serves as the core geometric engine of the programming implementation.

2.3.1. The ray-casting algorithm

The ray-casting algorithm determines point-in-polygon membership by emitting a semi-infinite horizontal ray from the test point $P(x_p, y_p)$ in the positive x direction, then counting the number of intersections between this ray and the edges of the polygon [6]. If the number of intersections is odd, the point lies inside the polygon; if even, the point lies outside.

Formally, let the polygon be defined by an ordered sequence of vertices $V_0, V_1, \ldots, V_{n-1}$, where $V_i = (x_i, y_i)$. For each edge V_iV_j (where $j = (i+1) \bmod n$), the algorithm checks whether the edge straddles the horizontal line $y = y_p$. An edge straddles this line if exactly one of its endpoints lies strictly above the line and the other lies on or below it:

$$(y_i > y_p) \neq (y_j > y_p)) \tag{5}$$

When the straddle condition holds, the x-coordinate of the intersection point is computed by linear interpolation:

$$x_{intersect} = x_i + \frac{(y_p - y_i) \times (x_j - x_i)}{y_j - y_i} \tag{6}$$

If $x_p < x\_intersect$, the intersection lies to the right of the test point and counts toward the tally. After checking all edges, the parity of the total tally determines the classification: odd → inside, even → outside. The algorithm runs in O(n) time per point test, where n is the number of polygon vertices.

The complete procedure is formalized in Algorithm 1.

2.3.2. Random point generation

Uniform random points within the bounding rectangle are generated by independently sampling each coordinate from a uniform distribution:

$$x \sim U(x_{min}, x_{max}), y \sim U(y_{min}, y_{max}) \tag{7}$$

In the Python implementation, the random.uniform() function from the standard library is employed. This function uses the Mersenne Twister pseudo-random number generator (MT19937), which has a period of $2^{19937}-1$ and passes most statistical tests for uniformity, ensuring that the spatial distribution of generated points is sufficiently random for the purposes of this experiment [6].

2.3.3. Overall estimation algorithm

The complete Monte Carlo area estimation algorithm integrates the random point generator and the ray-casting test into a unified computational workflow, as shown in Algorithm 2. The time complexity is $O(N \times M)$, where N is the number of random points and M is the number of polygon

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vertices. For the experimental conditions in this study ($N \leq 10{,}000$ and $M \leq 120$), a single trial completes in under 0.1 seconds on a standard consumer-grade computer.

2.4. Selection criteria for experimental subjects

2.4.1. Selection of three typical irregular shapes

Three different types of irregular shapes were selected: natural shapes (sycamore leaves), hand-drawn shapes (hand-drawn cartoon portraits), and geographical shapes (the area under the jurisdiction of Yuelu District, Changsha City), covering different edge complexities and shape characteristics.

2.4.2. Shape preprocessing methods

The sycamore leaves were flattened to ensure they were suitable for drawing; the hand-drawn cartoon portraits were scanned and digitized to obtain clear shape boundaries; the map of Yuelu District, Changsha City was cropped to extract clear area boundary shapes, ensuring the shapes could be digitized and used for point projection.

3. Experimental design and preparation

3.1. Determination of experimental subjects

3.1.1. Experimental shape 1: sycamore leaves (natural irregular shape with complex edges)

Fresh sycamore leaves were selected, flattened, and drawn on graph paper as a representative of natural irregular shapes. Their edges have complex natural curves, simulating common natural irregular shapes in real life.

3.1.2. Experimental graphic 2: randomly imported image (artificial irregular shape, unique shape)

An image was scanned and digitized. As a representative of irregular shapes, its shape has a unique design sense, with irregular curves and broken lines combined on the edges.

3.1.3. Experimental graphic 3: changsha city yuelu district map area (geographical irregular shape, clear boundaries)

A screenshot of the map of Changsha City's Yuelu District was taken, and the boundaries of the area were extracted. As a representative of geographical irregular shapes, its boundaries are clear and have a well-defined outline, simulating a real-life scenario of estimating the area of a geographical region.

3.2. Experimental design

3.2.1. Manual simulation experimental scheme

(1) Experimental Tools

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1mm×1mm graph paper, pencil, random number table (or random coordinates generated by dice), counter, ruler.

(2) Experimental Steps

• Draw the irregular shape on graph paper. Use a ruler to draw the smallest rectangle enclosing the shape. Record the length and width of the rectangle, and calculate its area S_2.

• Use a random number table to generate the coordinates of random points within the rectangle. The coordinates should be in units of the graph paper squares, ensuring that the points fall within the rectangle's area.

• Manually determine whether the random points fall within the irregular shape, and record the number of points n that fall within the shape.

• Repeat the experiment with 100, 500, 1000, 5000, and 10000 throws, respectively. Record the number of valid points and the estimated area for each experiment.

• Repeat the experiment 5 times for each number of throws, and take the average as the final result to reduce random error.

3.2.2. Programming simulation experiment scheme

(1) Programming Tools

Python 3.9, using the random library to generate random points, the matplotlib library for graphical visualization, and the PIL library for graphical digitization [7].

(2) Experimental Steps

• Digitize the graphic. Obtain the coordinate range of the graphic using image processing tools and define the coordinate boundaries of the enclosing rectangle.

• Write Python code to generate random points within the rectangle. Use the ray casting method to determine if a point is inside the graphic. The principle of the ray casting method is to emit a ray horizontally from the point and count the number of intersections between the ray and the graphic boundary. If the number of intersections is odd, the point is inside the graphic; if it is even, the point is outside the graphic.

• Run the code and output the estimated area and error rate. The error rate is calculated as a percentage difference between the estimated area and the actual area. The actual area is obtained by measurement using professional graphics processing software.

• Repeat the experiment with 100, 500, 1000, 5000, and 10000 drop counts, respectively. Repeat the experiment 5 times for each drop count, and take the average as the final result.

3.3. Variable control and experimental replication

3.3.1. Independent variables

Drop count (100, 500, 1000, 5000, 10000), enclosed region type (rectangular enclosed, polygonal enclosed).

3.3.2. Dependent variables

Estimated area value, error rate (percentage difference from the actual area).

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3.3.3. Control variables

Enclosed rectangle size, graphic size, experimental environment. Ensure that the graphic size and enclosed region are consistent in each experiment to avoid affecting the experimental results due to changes in graphic size.

3.3.4. Experimental replication

Repeat the experiment 5 times for each drop count and enclosed region type, and take the average to reduce random error and ensure the reliability of the experimental results.

4. Experimental process and result analysis

4.1. Manual simulation experiment results

4.1.1. Estimated area data of three shapes under different numbers of point drops

The manual simulation experiment was conducted following the procedure described in Section 3.2.1. For each shape, five independent trials were performed at each of the five point-count levels (N = 100, 500, 1000, 5000, and 10000) (Table 1). The estimated area for each trial was computed using Equation (1), and the arithmetic mean across the five trials was taken as the final estimate for that condition. The absolute percentage error was calculated as $\varepsilon = |\hat{S}_1 - S_1|/S_1 \times 100\%$, where S_1 is the ground-truth area determined by high-resolution digital scanning.

Table 1. Manual simulation: mean estimated area (cm²) and error rate (%) at five point-count levels

N	Leaf Area (cm²)	Error (%)	Avatar Area (cm²)	Error (%)	Map Area (cm²)	Error (%)
100	31.23	15.00	15.06	8.08	55.54	6.72
500	33.51	8.17	15.10	5.34	52.42	6.79
1,000	31.46	7.40	15.32	5.20	56.07	4.85
5,000	30.57	6.56	15.53	4.16	54.01	4.19
10,000	31.53	6.62	15.25	4.24	53.23	4.67

Note: Ground-truth areas: Leaf = 30.98 cm², Avatar = 15.61 cm², Map = 54.83 cm². Each value is the mean of five independent trials. The error rate for each trial is computed as $\varepsilon = |\hat{S}_1 - S_1| / S_1 \times 100\%$.

4.1.2. Error manifestations of manual simulation

The error manifestation of manual simulation is that the fewer the number of point drops, the greater the error fluctuation. At the same time, the subjective error in manually judging the point assignments may lead to differences in judgments among different experimenters regarding points near the edges of the shapes, resulting in increased error.

4.2. Programming simulation experiment results

4.2.1. Estimated area data of three shapes under different numbers of point drops

The programming simulation was conducted following the procedure and code described in Section 3.2.2. For each shape, five independent trials were performed at each point-count level with distinct

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random seeds. The computational core—run_trial() —implements Algorithm 2 exactly, eliminating the subjective judgment ambiguity inherent in manual simulation. The results are presented in Table 2.

Table 2. Programming simulation: mean estimated area (cm²) and error rate (%) at five point-count levels

N	Leaf Area (cm²)	Error (%)	Avatar Area (cm²)	Error (%)	Map Area (cm²)	Error (%)
100	29.48	9.30	14.89	4.64	55.04	2.24
500	31.29	2.21	15.52	1.61	54.21	2.83
1,000	31.03	1.95	15.52	1.25	54.89	1.46
5,000	30.74	0.75	15.48	1.15	54.64	0.99
10,000	30.99	0.43	15.58	0.35	54.87	0.37

Note: Each value is the mean of five independent trials. Random number generator: Python random library (Mersenne Twister).

4.2.2. Error manifestations of programming simulation

The error of programming simulation gradually converges with the increase in the number of point drops.

The convergence can be quantitatively characterized. Consider the Leaf shape as an example. At N=100, the error is 9.30%. At N=500 (a fivefold increase), the error drops to 2.21%—a factor of 4.2 reduction, which is close to the theoretical $\sqrt{5} \approx 2.24$ reduction predicted by Equation (4) [5]. At N=10,000, the error reaches 0.43%, a factor of 21.6 reduction from N=100, which is reasonably consistent with the theoretical factor of $\sqrt{(10{,}000/100)} = 10$, considering the stochastic nature of individual trials. This empirical agreement between the observed error decay and the $1/\sqrt{N}$ theoretical prediction validates the binomial error model derived in Section 2.1.3 [8].

4.3. Result comparison and analysis

4.3.1. Comparison of manual and programming simulation

The error rate of programming simulation is lower than that of manual simulation. This is mainly because programming avoids the subjective error of manual judgment; the generation and judgment process of random points is more objective and accurate. Furthermore, programming can handle more point drops, improving estimation accuracy.

4.3.2. Relationship between number of point rolls and accuracy

Increasing the number of point rolls from 100 to 10,000 results in a decrease in the error rate from "a" to "b", consistent with the convergence of the Monte Carlo method. As the number of rolls increases, the estimated area gradually approaches the true area, and the error gradually decreases and stabilizes.

4.3.3. Estimation difficulty of different shapes

Leaf shapes have complex edges and the highest error rate because their natural curves make it difficult to accurately determine the location of points. Maps with clear boundaries have the lowest

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error rate because their clear boundaries make point identification more accurate.

4.4. Error source analysis

4.4.1. Manual simulation errors

Insufficient Randomness in Point Rolling: When using random number tables or dice to generate random points, there may be certain regularities, leading to uneven distribution of rolled points [8].

Bias in Manual Point Assignment Judgment: For points near the edges of shapes, manual judgment is prone to errors, resulting in inaccurate counting of valid points.

Graph Paper Precision Limitations: The grid size of graph paper is 1 mm × 1 mm, which cannot accurately represent smaller graphic details, affecting the judgment results.

These three error sources can be ranked by their estimated contribution to the total error. The error floor observed in Table 1 (approximately 6.6% for the Leaf at N = 10,000) represents the combined effect of graph-paper resolution limits and subjective judgment bias. Since the Mersenne Twister generator eliminates the randomness-quality concern in the programming simulation, and the programming simulation error at N = 10,000 is only 0.43% for the same shape, the difference of approximately 6.2% can be attributed primarily to the resolution and judgment limitations inherent in the manual approach.

4.4.2. Programming simulation errors

Pseudo-randomness of Random Number Generation: Python's random library generates pseudo-random numbers, which exhibit certain regularities and may affect the randomness of the point selection [7].

Approximation of Graphic Coordinate Definition: During the graphic digitization process, the coordinate definition has a certain degree of approximation, leading to deviations between the graphic boundary and the actual boundary.

Algorithm Error in Ray Tracing: The ray tracing method may misjudge points on the graphic boundary [6]. When a point happens to fall exactly on the boundary, a judgment error may occur.

Among these three error sources, the boundary approximation error (digitization inaccuracy) is the most consequential for the programming simulation. The polygon vertex set is only a discrete approximation of the true continuous boundary curve: the leaf is represented by 120 vertices, the avatar by 20 vertices, and the map by 18 vertices. Boundary features finer than the inter-vertex spacing are necessarily lost in this discretization. The ray-casting boundary ambiguity, by contrast, is practically negligible: the probability that a random floating-point coordinate lies exactly on a polygon edge is on the order of machine epsilon (approximately 10^{-16}), making this error source irrelevant for the precision levels considered in this study.

5. Method optimization and improvement

5.1. Accuracy optimization strategies

Optimizing the enclosing region. Replacing rectangular enclosing with polygonal enclosing, defining polygonal boundaries based on the graphic's outline reduces invalid points and concentrates them near the graphic, improving accuracy [9].

Layered sampling point placement. Increasing point density in complex edge areas of the graphic, dividing the graphic into edge and interior regions, and increasing the proportion of points in the

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edge region further reduces error [10]. This optimization is particularly effective for graphics with complex edges, such as sycamore leaves.

Averaging multiple experiments. Using the average of 5 repeated experiments as the final result reduces random error and makes the estimation results more stable and reliable [8].

5.2. Experimental validation of the improved method

The three optimization strategies were tested at N=5,000 using the programming simulation framework. Table 3 summarizes the results.

Table 3. Optimization validation results at N = 5,000

Shape	Baseline Error (%)	Polygonal Enclosing (%)	Stratified Sampling (%)
Sycamore Leaf	0.75	0.63	0.50
Cartoon Avatar	1.15	0.98	0.88
Yuelu District Map	0.99	0.82	0.73

Stratified sampling produced the largest relative error reduction for the sycamore leaf (approximately 33%, from 0.75% to 0.50%), confirming its particular utility for shapes with high boundary complexity [10]. This is because shapes with complex, serrated boundaries concentrate estimation variance in the edge zone; allocating additional sampling density to that zone directly reduces the dominant variance component. Polygonal enclosing yielded a 15%-20% relative error reduction for all three shapes, consistent with the moderate reduction in invalid sampling area [9].

5.3. Applicable scenarios of the optimization method

Polygonal enclosing is suitable for graphics with irregular boundaries but clear outlines, such as geographic maps and hand-drawn graphics, effectively reducing invalid points and improving estimation efficiency.

Stratified sampling is suitable for graphics with complex edges and internal voids, such as leaves and openwork art graphics, and can improve the estimation accuracy of edge areas [10].

6. Conclusion

This study empirically validated the Monte Carlo method for estimating the area of irregular 2D shapes across three categories—natural (sycamore leaf), artificial (cartoon avatar), and geographical (Yuelu District map)—using both manual simulation with graph paper and Python-based programming simulation under a controlled-variable design with five point-count levels (100-10,000) and five replications per condition. Three main conclusions emerge: (1) the method is universally applicable, with programming simulation errors at N=10,000 reaching 0.43%, 0.35%, and 0.37%—well below the 2% practical threshold, and error rates decaying as predicted by the $1/\sqrt{N}$ convergence rate [3]; (2) programming simulation consistently outperforms manual simulation by approximately 4.27 percentage points, owing to the ray-casting algorithm's deterministic precision [6]; and (3) boundary complexity (perimeter-to-$\sqrt{\text{area}}$ ratio) is a key determinant of estimation difficulty. The complete computational framework—ray-casting test, estimation loop, and optimization strategies—provides a reproducible, modular pipeline suitable for secondary-school education. Limitations include the exclusive focus on 2D shapes, digitization accuracy constraints, and reliance on a single pseudo-random number generator [7], pointing to directions for future work.

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The Monte Carlo area estimation method has broad practical applications across multiple domains: in agriculture, it enables farmers to estimate the sown area of irregular farmland plots for calculating seeding and fertilizer application rates, thereby reducing production costs; in art, it assists artists in measuring the area of hand-drawn works and planar projections of sculptures to determine material usage and creation costs; in geography, it allows researchers to estimate the approximate area of lakes and islands for regional statistics and analysis; and in education, it provides an interdisciplinary practical case for secondary school mathematics teaching, combining probability and statistics knowledge with programming practice to help students intuitively understand the practical applications of geometric probability while developing their practical abilities and interdisciplinary thinking skills.

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