The Function Integral Inequality and Its Application are Proved by Multiple Integral

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Abstract: The calculation of traditional method of using the multiple integral to prove the function integral inequality is too large, and the calculation error is easy to occur. In this regard, the Monte-Carlo simulation numerical calculation method of multiple integral is proposed. It adopts the principle of Monte Carlo average calculation method, and improves the original average calculation method by linearly overlapping the integral regions. Then, it extends the integral mean algorithm of the rectangular integral region to the integral numerical calculation of the function integral, and realizes the proof of function integral inequality. Through calculation and evaluation, it can be determined that the Monte-Carlo simulation numerical calculation method of multiple integral can effectively reduce the computational efficiency of the function integral inequality proof. The calculation program is simple and is easy to calculate and debug, which has practical application value.

Keywords: Multiple integral; Function integral; Monte Carlo

1. Introduction

The proof of function integral inequality in the traditional mathematics field involves the calculation of multiple integrals. For such calculation problems, the difficulty of computational proof will continue to rise geometrically as the computational dimension increases. Traditional numerical algorithms are difficult to directly use the multiple integral to prove function integral inequality. Monte Carlo integral mean calculation method is also called stochastic simulation method or integral statistical data experiment method. Based on the probability statistics theory, the algorithm relies on the numerical principle of the law in mathematics, and uses computer numerical simulation to solve the integral calculation method of the complexity calculation problem which is difficult to directly calculate by mathematical method. The method mainly uses stochastic integral numerical simulation and statistical experiments as the means to generate a random numerical sequence of probability distribution characteristics that is more in line with the integral random variable through the selection of random integral values, and conduct simulation experiments as a specific variable sequence. When applying the Monte Carlo algorithm, it is necessary to ensure that the integral value produces a uniform random sequence as the input variable sequence and directly perform the sequence proof simulation experiment [1].

Today, the solving multiple integral inequalities of Monte Carlo method are mostly developed towards more mature pointing methods and mean measurement methods. Because of the calculation of the overall error is large and cumbersome, the pointing method's application range is narrow. On the basis of the integral uniform random number, the mean method uses the regional algorithm multiple integral to carry out solving, and the overall calculation result is simple and good [2]. Taking Monte Carlo method as the core, the calculation method is improved by using the integral region feature of multiple integral, and then the function integral inequality is proved.

2. Analysis and Method of Multiple Integral Calculation Algorithm

2.1. Analysis of trouble integral algorithm

The integral can be regarded as the mathematical expectation of a random variable, so when using the Monte Carlo method to perform the multiple integral calculation, the random variable mean algorithm is needed to approximate the value [3].

Let $f(\mathrm{x},\mathrm{y})$ be the bounded function value above the region D, so we need to use the general stochastic differential function value $\int f(\mathrm{x},\mathrm{y})d\mathrm{x}d\mathrm{y}$:

Take a holding region $N: a \le \mathrm{x} \le b, c \le \mathrm{y} \le d$, containing a specific value range and D, take any function $g(\mathrm{x},\mathrm{y})$ with a significant probability density, satisfying $\int g(\mathrm{x},\mathrm{y})d\mathrm{x}d\mathrm{y} = 1$;

(x, y), $i = 1, 2, 3, \mathbf{K}, n$, n is a random number sequence with $g(x, y)$ as the probability density. Let (x, y), $i = 1, 2, 3, \mathbf{K}, k$, k be the k inequalities random numbers in D, when n has an infinite value, the equation can be derived:

$$\iint f(x, y)dxdy \approx \frac{1}{n}\sum_{i=1}^{k}\frac{f(x, y)}{g(x, y)} \quad (1)$$

According to formula (1), the following proof is given:
Le (x, y) be a random dependent variable with $g(x, y)$ as the overall probability density [4]. (x, y), $i = 1, 2, 3, \mathbf{K}, n$,is a set of test samples of (x, y),$(Xi, Yi) = 1, 2, \mathbf{K}$ is the corresponding sample observation value:

$$f(x, y) = \begin{cases} f(x, y), (x, y) \in D \\ 0, (x, y) \notin D \end{cases} \quad (2)$$

$$f\frac{f(x, y)}{g(x, y)}g(x, y)dxdy = E\frac{f(x, y)}{g(x, y)} \quad (3)$$

From the formula (2) and formula (3) and the large number theorem, and according to the significance of statistical probability, the probability mean of the overall statistical mean limit of the random variable can be proved as the formula (1). If the overall integral region is a rectangular integral region of D for the double integral whose integral is the constant term, the overall area S is a constant term integral [5]. Assuming that the probability density $g(x, y) = 1/s$, the integral equation satisfies the condition (x, y) of $\int g(x, y)dxdy = 1$ as a whole. $i = 1, 2, \mathbf{K}$, N is an integral zone where the $g(x, y)$ is a uniform probability density on the indefinite integral region D, so the formula (1) can be further simplified to

$$\iint f(x, y)dxdy \approx \frac{s}{n}\sum_{i=1}^{N} f(x, y) \quad (4)$$

When using the formula (3) for the overall integral calculation, it is necessary to obtain the random function integer column $(r1, r2, r3, \mathbf{K}, rk)$ to substitute the integrand function and an integral variable cluster, and then it needs to perform the coincidence quadrature with the upper and lower lines of the corresponding integral for N times. When the value of N is large enough, the result obtained is the determined integral simulation result.

2.2. Improvement of double integral

For I=$f(x, y)$, the double integral is directly differentiated and accumulated according to the overall integration area, and the equation can be obtained

$$f(x, y)d = \int f(x, y)dxdy \quad (5)$$

Let d be a random number sequence between (0,1). From $x = a2ai + (b1 - a2)r$, it can be seen that the interval of the unknowns is A and B. In the interval, the unknowns are uniformly distributed, thereby ensuring that all random number sequences are random number sequences on the integral region D, and the overall distribution probability is S[6]. This requires the introduction of integral median analysis:

If the function $f(x)$ has a continuous effect in the closed interval AB, then there must be a fixed point C in the entire integral interval AB, resulting in the presence of A, B, C greater than or equal to the governing system. In addition, within the integral interval, there is a bounded B region, the entire region has a continuous effect on the continuous data D, and E is the area of the region of D. Moreover, there must be a point in D, making the above relationship established. It is assumed that there is no continuous region in the closed region D in the function $f(x, y)$, and the area of D includes a plurality of zero points. Then there is a point in the D area to ensure that the above relationship is established. It is assumed that the continuous range of values in this interval are a and b. In the range, M is the maximum value and the minimum value is m. The maximum and minimum values are simultaneously taken into equation (5) and then divided by $(b - a)$ so that the formula matrix can be used according to the medium theorem of the continuous function:

$$A = \begin{bmatrix} -(l_{12} + l_{13}) & l_{12} & l_{13} & 0 & 0 \\ m_{12} & -(m_{12} + l_{24}) & 0 & l_{24} & 0 \\ m_{13} & 0 & -(m_{12} + l_{35}) & 0 & l_{35} \\ 0 & m_{24} & 0 & -m_{24} & 0 \\ 0 & 0 & m_{35} & 0 & -m_{35} \end{bmatrix} \quad (6)$$

The meaning of the set is to set a b c as the three line segments of the set image. The x-axis represents a and the y-axis represents b. The area of the trapezoid of the curved surface surrounded by a and b and the curve $y = f(x)$ is a line segment of length $(b - a)$. The most important function of the above theorem is to remove the integral symbol directly in the formula, or to re-function the most complex integrals to form a relatively simple odd function, thus simplifying the function problem. Therefore, for the equation or inequality that proves a function integral, or the definite integral in the target conclusion that needs to be proved, and the definite integral exists in all the limit formulas, the above integral method can be used to remove the integral number, or to be solved as the odd number function [7].

3. Use the Multiple Integral to Prove Function Integral

The variable value SUM is designed as 0, and the N assignment of each function is provided for the random function, needing to remove the maximum variable value of N. When the value of N is in the range of 0 to 1, a random uniform sequence r $(r1, r2, r3, \mathbf{K}, rk)$ is established, and the subscript k of the sequence is the number of sequence r's values. There is a formula (6) that calculates the mean domain interval of the entire sequence and solves the corresponding function sequence. The logical tree analysis method is introduced based on function sequence.

The current intrinsic unknowns have a significant differentiation significance for the way of function integral inequalities. The overall calculation amount is too large, and because the integral number is too large, the overall calculation is difficult. Therefore, the design uses a Hot Spare gate (HSP) to indicate the proof of the internal unknowns of the double integral. In addition, the logic tree is a new type of logic operation structure calculated or introduced for a large number of unknown parameters. The multiple integral and function integral are introduced internally into the integrand modules QD and DO, respectively. Because in the actual calculation, QD and DO modules may have misoperation effects, and QD causes the computational variance of the integrand before the DO module. In order to improve the dynamic fault tree model analysis logic, the dynamic gate logic can be transformed into the Markev dynamic analysis chain, as shown in Figure 1.

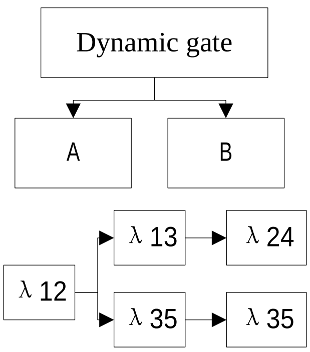

Figure 1. Function Integral Logic Dynamic Analysis Chain Transformation Diagram

From Figure 1, it can be seen that in the analog state, when the output result of the multiple integral is a failure, and neither A nor B fails or the failure rate of B is greater than A, the output result is not invalid. In addition, the value of l_{12}, l_{13}, l_{24}, l_{35} and others in Figure 1 are transition probabilities of multiple integral and function integral. Set

$l_{12} = l_{13} = l_{24} = l_{35} = 3.5752\times10^{-5} / h$

$m_{12} = m_{13} = m_{24} = m_{35} = (1/8)/h$,

According to the above values, the Markev dynamic analysis chain equation can be established corresponding to the model of Figure 1, which can calculate the inequality conversion of the double integral and the function integral.

4. Example Results and Analysis

In order to more accurately measure whether the double integral improvement based on Monte Carlo method can prove the function integral inequality more quickly, two specific integration regions are selected to establish different integrand equations for the analysis and comparison of double integral. The comparison result is 1000 different random numbers. For each additional 100 random numbers, one calculation result can be generated, and each calculation result has its obvious uniqueness. The Monte Carlo method is used to calculate the first set of integral. The analysis of Figure 2 is: according to the definition of double integral, the whole integral region can be clarified by the area surrounded by $x = 1$, $x = 2$, $y = x2$, so the function integral inequality of the whole random number distribution region can be directly proved.

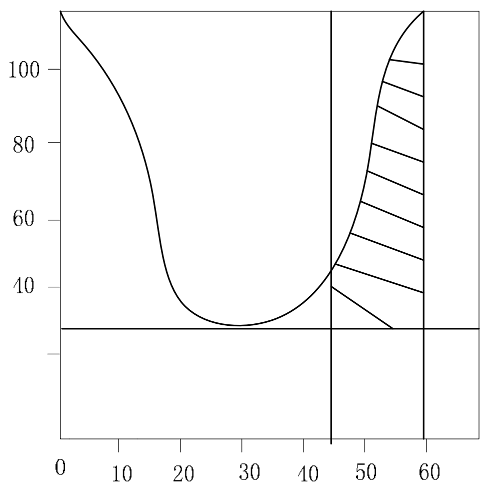

Figure 2. Schematic Diagram of Function Integral and Random Number Distribution

The calculation result is compared with the overall calculation accuracy value, and the more the random number value, the better the proof effect.

5. Conclusion

In the actual calculation process, the linear differential calculation method is adopted as a whole to obtain the random number, and the application of the design step can solve the better linear result of double integral. When the number of extracted samples is N, the overall calculation amount is continuously superimposed, and the calculation accuracy is also increased, but the two are not completely proportional. From the simulation results of

Figure 2, it can be calculated that when the N value is 700, it is the best simulation data. The improved Monte Carlo method is used to prove the function integral inequality with small overall error and ideal calculation result.

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