The Impact of T-Consciousness Fields on One-Dimensional Monte Carlo Computations (Integral)

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Abstract

The impact of T-Consciousness Fields (TCFs) on Monte-Carlo computations was initially investigated through the patterns obtained from the distribution of random values that were generated by different hardware and software combinations. In this section, we show the effect of TCF1 and TCF2 on the calculations performed for one-dimensional integral problems, where generated values are in the range of zero to one. This is, in fact, one application of the distribution of generated random numbers by which a specific integral in one dimension can be computed. This level of initial progress in the test paved the way for examining the effect of the previous study at a more advanced level. The results show an evident impact of TCF1 on the performed calculations, with an increase of approximately 2% in values close to the analytically predicted solution. Moreover, the total entropy of the interval for sample 1 and sample 2 increased by approximately 3% compared to that of the control.

Keywords: T-Consciousness Fields, Random Numbers, Monte Carlo, Integral

Introduction

The theory of T-Consciousness Fields (TCFs) was proposed by Mohammad Ali Taheri over four decades ago [1]. In recent years, extensive studies have been performed to verify and investigate the effect of such fields on living and non-living entities [2-3]. Monte Carlo simulations and random number generations are other interesting areas where one can study the impact of TCFs. This simulation method is based on random sampling and encompasses a set of computational techniques for solving mathematical problems, often in an approximate manner. It has been used in a wide range of fields, including mathematics, physics, biology, engineering, and finance, where finding an analytical solution is highly time-consuming. Since its introduction, Monte Carlo simulation helped in assessing the probability of different outcomes and risk management in many real-life scenarios, such as artificial intelligence (AI), stock prices, sales forecasting, weather prediction, project management, pricing, etc. [4]. This study is based on approximate integral calculations using sets of random numbers generated using Monte Carlo simulations.

Method

As previously mentioned in section 2-2-2 of the 'Common Considerations', one-dimensional integral has been calculated using a set of random numbers. At first, a descriptive analysis of all the values obtained was conducted for the control and the two samples. Then, with binning at 0.002 intervals, the distribution of the values for each category was built and compared with each other.

Results and Conclusions

In this study, one-dimensional integral calculations, performed by generating a series of random numbers, were compared in control and sample groups. Initially, a descriptive statistical analysis of the values in the studied groups was conducted, which is shown in Table 1. Here, the rows highlighted in cyan represent central tendency measures. Considering the proximity of the values and the standard error of the mean, significant changes cannot be observed upon the exposure of the generated random numbers to TCF1 and TCF2. The box plot provided in Figure 1 illustrates the drift of all the computed values from the analytical value.

Table 1 - Descriptive analysis of integral calculations in samples and controls

	Control	TCF1	TCF2
Number of values	100	100	100
Minimum	0.989	0.984	0.989
25% Percentile	0.995	0.996	0.996
Median	0.999	1.000	0.999
75% Percentile	1.000	1.000	1.000
Maximum	1.010	1.010	1.010
Range	0.023	0.024	0.024
Actual confidence level	96.5%	95.6%	96.5%
Lower confidence limit	0.998	0.999	0.998
Upper confidence limit	1.000	1.000	1.000
Mean	0.999	0.999	1.000
Std. Deviation	0.004	0.005	0.005
Lower 95% CI of mean	0.998	0.998	0.999
Upper 95% CI of mean	1.000	1.000	1.000
+1 Sigma (round 0.1) of Mean	1.000	1.000	1.000
-1 Sigma (round 0.1) of Mean	1.000	1.000	1.000

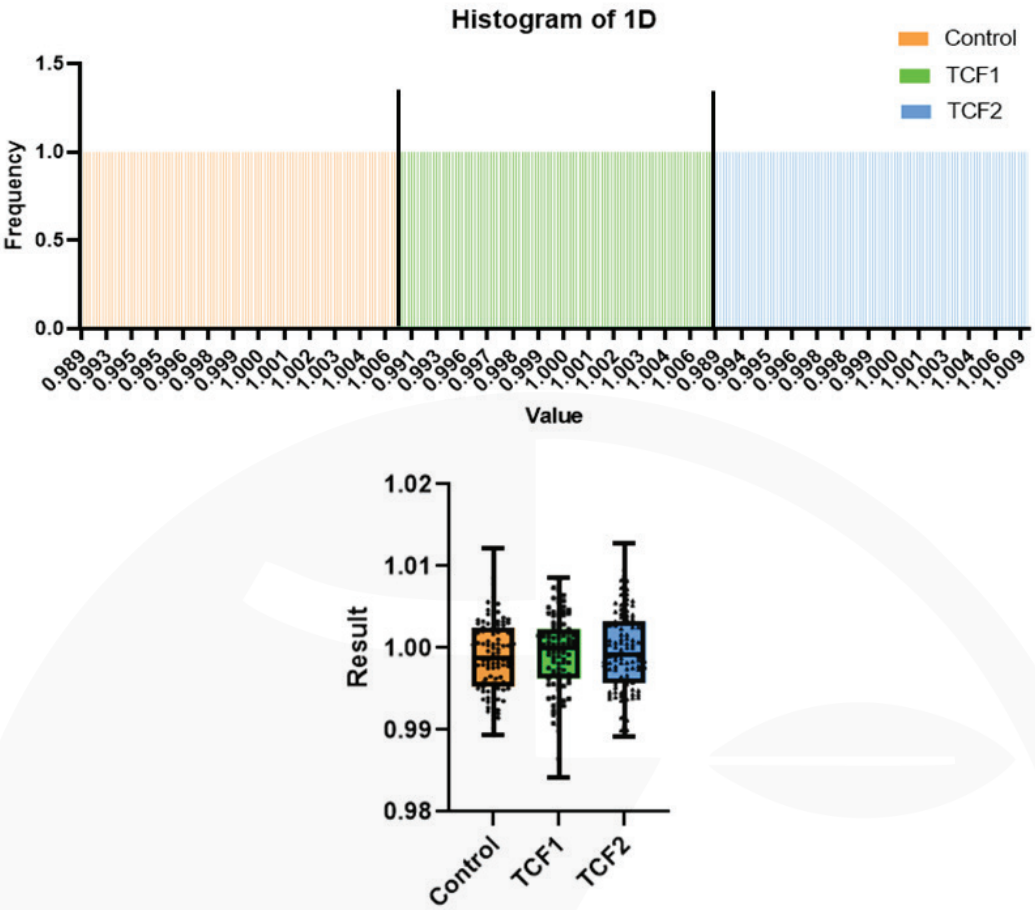

Figure 1. Histogram of all generated values (top) along with boxplot analysis of generated values (bottom).

A histogram of all the computed values in one dimension and their drifts from the analytical values are provided in Figure 1 (top and bottom), respectively. As can be seen in the top plot, the frequency of all the generated values within the selected range is equal to 1 for sample 1 and sample 2, as well as the control. The boxplot analysis of sample 1 and sample 2 (provided at the bottom figure) shows an overall drift towards higher values compared to the control. For sample 2, an upward trend in the boxplot of the data is evident.

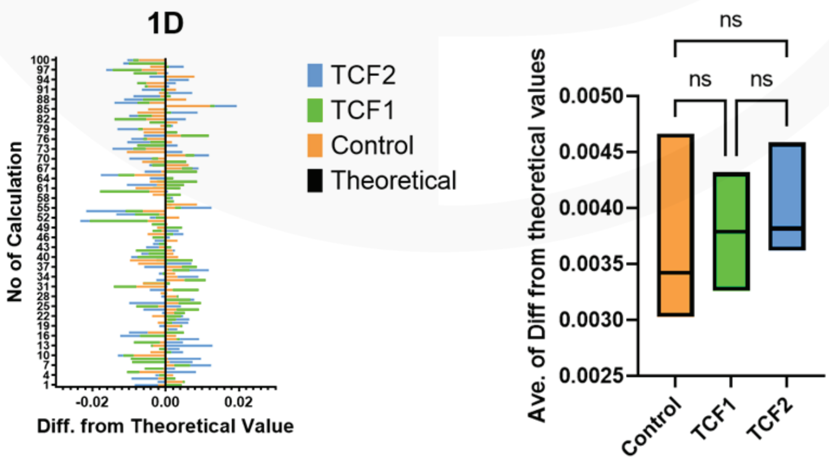

Figure 2. Illustrates a comparative display of the difference values between the calculated and analytical values in the control and samples in 100 rounds of calculations (the zero line indicates equivalence with the analytical value and zero difference). Additionally, it includes a boxplot analysis of the average uncertainty calculation in the control and samples with over three repetitions each.

In Figure 2 (left), a comparative display of the difference between the calculated and analytical values for the samples and the control group is provided. As can be seen, this drift varies in magnitude and distribution but remains within the range of non-significant (ns) difference (as observed with over three repetitions of each). Furthermore, the range of uncertainty variation (the difference between the calculated value and the analytical value) is lower in both samples than in the control group.

In Table 2, the frequencies of the generated numbers for selected intervals (bins) are compared between the control and the samples. In the first column, the analytical value is highlighted in blue. For calculating the nearest interval frequencies (with respect to the analytical value), one interval less and one interval more on both sides of the analytical value are color-coded. Furthermore, the total frequency of the calculated values in this range is calculated and mentioned at the bottom of Table 2. Regarding entropy, the Shannon entropy value for the entire range of values is calculated according to the equation provided in the 'common considerations' section (section 2-2-3).

Table 2 - Data categorized in the one-dimensional calculation test along with the calculation of the shannon entropy for the entire interval; the value specified in column 1 is the expected analytical value.

Bin Center	Control	TCF1	TCF2
0.984	0	1	0
0.986	0	1	0
0.988	0	0	0
0.990	2	3	5
0.992	8	7	2
0.994	10	6	15
0.996	14	12	7
0.998	17	11	20
1.000	15	19	16
1.002	14	18	9
1.004	13	10	11
1.006	4	6	8
1.008	2	5	5
1.010	0	0	1
1.012	1	0	1
Entropy	2.16	2.22	2.22
The percentage of calculation output in the closest intervals to the analytical value	46%	48%	45%

In Table 2, by categorizing the calculated numbers into different intervals and counting their occurrences in each interval, the frequencies of the estimated numbers in the control and the samples have been obtained. Since the expected analytical value in this study was determined to be 1, a special interval centered around 1 and its nearest intervals on both sides (highlighted rows) are considered as the closest regions to the expected answer. The frequency of the estimated numbers in this range (relative to the total calculations) is presented as the occurrence or count in the nearest region and is listed in the last row. As can be seen, the impact of TCF1 is evident, showing an increase of approximately 2% in the nearest range and being consistent with the analytical solution. Additionally, the overall entropy of the interval for both samples increased by about 3%, as compared to the control.

Further investigations related to the impact of TCFs on more complex computational scenarios are covered in the following sections.

References

1. Taheri, M. A. (2013). *Human from Another Outlook*. Interuniversal Press. 2nd Edition. ISBN-13: 9781939507006-, ISBN-10: 1939507006 2013.

2. Taheri, M. A., Payervand, F., Ahmadkhanlou, F., Torabi, S., & Semsarha, F. (2022). The Effect of Taheri Consciousness Fields on the ATP Production in HEK-293 Cell Line by Measuring Luciferase Activity. *Journal of Cosmointel, 1*(9), 3455-.

3. Taheri M. A., Payervand F., Ahmadkhanlou F., Torabi S. & Semsarha F. (2021). Distinction of Consciousness Fields According to Taheri from Other Conventional Physical Fields: Evaluating the Magnetic Properties of Materials. *Research Square*. DOI: 10.21203/rs.3.rs-618789/v3. https://assets-eu.researchsquare.com/files/rs-618789/v3_covered.pdf?c=1631875952

4. Johansen, A. M. (2010). Monte Carlo Methods. International encyclopedia of education, *Elsevier* 296-303.