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Random number generators and causality

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Abstract

We advance a prescription to randomize physical or algorithmic Random Number Generators (RNG's) *that do not pass* Marsaglia's DIEHARD test suite and discuss a special physical quantifier, based on an intensive statistical complexity measure, that is able to adequately assess the improvements produced thereby. Eight RNG's are evaluated and the associated results are compared to those obtained by recourse to Marsaglia's DIEHARD test suite. Our quantifier, which is evaluated using causality arguments, can forecast whether a given RNG will pass the above mentioned test.

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1. Introduction

Random Number Generators (RNG) are extensively used in physics and engineering. In point of fact, most computer systems possess RNG's, although not all of them are of good enough quality for statistical purposes. Recourse to special physical devices is also made so as to produce RNG's. It is then appropriate to classify RNG's as either "physical" or "algorithmic" ones. A very important RNG-issue is its adequate testing for specific applications such as encryption schemes and/or sophisticated Monte Carlo simulations. An easily available and very stringent statistical test-suite is that provided by Marsaglia [1]. In his website one finds two impressive contributions to the problem: (a) an RNG obtained by *mixing* algorithmic and physical generators, and (b) a complete RNG-test suite (called "DIEHARD"). The above referred to mixing is required because, quoting Marsaglia, "no physical devices I have considered pass the stringent randomness requirements of my DIEHARD battery of tests. But the deterministic methods do". In fact, he used the algorithmic RNG's to get good statistical properties and the physical devices to make the RNG's unpredictable.

In physics one assumes that a model can be manufactured for any system of interest and, in a sense, unpredictability may be understood as meaning that the model's features are not already known in sufficient detail. Furthermore, a complex dynamics does not imply a complex model if nonlinearity is present; low-dimensional chaotic dynamical systems are nice examples of such an assertion. Consequently, chaotic systems are good candidates to model devices used to produce physical RNG's.

The latest available version of Marsaglia's DIEHARD produces a matrix with about three hundred values as a *Test Summary*. These values are expected to be distributed in a rather close fashion to the uniform distribution in the interval $[0, 1)$.

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A global quantifier is also provided by a KStest (Kolmogorov–Smirnov test) for the same interval.

The present effort purports to effect two main contributions to the above, ongoing discussion: (1) a prescription to randomize those physical or algorithmic RNG's *that do fail to pass* the DIEHARD test suite; and (2) advancing *the use of a special physical quantifier*, based on an intensive statistical complexity measure (MPR statistical complexity [2–5]), to assess the improvements achieved by recourse to the prescription of (1) above. This quantifier takes causality effects into account. Eight RNG's are evaluated and the concomitant results are compared to those obtained by recourse to Marsaglia's DIEHARD test suite.

Our work should be of relevance for Monte Carlo simulations [6], cryptography [7], communications theory [8] and some aspects of nanotechnology [9]. From a theoretical point of view it is of interest to point out that we are here linking the concept of Kolmogorov–Chaitin's algorithmic complexity [10] with that of *statistical* complexity. The former is adequately treated according to the so-called Pompe [11] procedure, adopted in this Letter to assign a probability distribution P to a given time series.

2. Methodology

In a recent contribution, López-Ruiz, Mancini and Calbet (LMC) have proposed a statistical complexity measure (SCM) based on the notion of "disequilibrium" as a quantifier of the degree of physical structure in a time series [12]. Given a probability distribution associated with a system's state, the LMC measure is the product of an entropy H times a distance to the uniform-equilibrium state Q. It vanishes for a totally random process. Martín, Plastino and Rosso (MPR) [2] improved on this measure by modifying the distance-component (in the concomitant probability space). In Ref. [2], Q is built-up using Wootters' statistical distance while H is a normalized Shannon-entropy. Regrettably enough, the ensuing statistical complexity measure is neither an intensive nor an extensive quantity, although it yields useful results [3]. Also, a reasonable complexity measure should be able to distinguish among different degrees of periodicity and it should vanish only for periodicity unity. In order to attain such goals any natural improvement should give this statistical measure an intensive character. Lamberti, Martín, Plastino and Rosso [4] obtained a statistical complexity measure (SCM) that is (i) able to grasp essential details of the dynamics, (ii) an intensive quantity, and (iii) capable of discerning among different degrees of periodicity and chaos. Such complexity measure is the one to be employed here to deal with RNG's. It has been shown in Refs. [3,4] that the MPR intensive statistical complexity measure provides one with more detailed information than the one obtained using just Shannon's entropy, which may confuse high degree of chaoticity with randomness.

Evaluation of the probability distribution P associated to a dynamical system or time series under study is a physical problem. Additional improvements can be expected if the underlying probability distribution is "extracted" by more appropriate consideration regarding causal effects in the system's dynamics.

The essence of symbolic dynamics is to associate a symbol sequence with each trajectory of a continuous or discrete dynamical system, by means of a suitable partition of the state-space. This process is described in the context of a *delay-embedding* of the time series into a d-dimensional space in Ref. [13]. Special generating partitions yield in the limit for a fine resolution the Kolmogorov–Sinai entropy. But these partitions are very difficult to ascertain even in the case of two-dimensional systems. Bandt and Pompe [11] advanced a method that "naturally" determines the adequate symbol sequence from the time series' values, without further model assumptions. They determine partitions of the state-space given by comparison of neighboring series' values. For any given series they look for certain *ordinal patterns* of order d. From the symbol occurrence frequency, they deduce a *permutation* probability distribution [11,14,15]. The advantages of Bandt and Pompe's method reside in (i) its simplicity, (ii) extremely fast calculation-process, (iii) robustness, and (iv) invariance with respect to nonlinear monotonous transformations. Using Kolmogorov–Chaitin's algorithmic complexity is another recourse that could be taken advantage of to overcome these problems, although this poses is much more difficult task.

All the RNG's assessed in this Letter are deterministic but *some* of them come from "discretised" chaotic differential equations that may be thought of as models for real physical processes (physical RNG's) while *others* come from recurrence rules (algorithmic RNG's). In order to convert any of them into an electronically realizable RNG, the following scheme is to be applied. (Step 1): a discretising process followed by a biased, scaling transformation that transforms our RNG-"signal" into natural numbers belonging to the interval $[0, 2^n - 1]$; after this step, each random number can be regarded as an n-bit word. (Step 2): a bit stream is assigned to each word. The length of this bit stream can be selected in different ways, the simplest one being to use all the bits of each word (ALL version). By generating five-million 16-bits-words we obtain an 80 million bit stream. We demonstrate below that this procedure yields poor results. It is much better to store just a portion of each word. In this Letter we follow, two strategies: (a) we use, for each n-bit-word's, only the *most significative* bit[1] (MSB version) to generate the bit stream. This is equivalent to the standard symbolic dynamic procedure of assigning a "1" if the number belongs to the range $[2^{n-1}, 2^n - 1]$ and a "0" if it lies within $[0, 2^{n-1} - 1]$. (b) Pick up, for each n-bit-word's, only the *least significative* bit (see footnote 1) (LSB version) to generate the bit stream. This bit represents a small perturbation and our results show that option LSB is the best one because it eliminates low frequency components of the Fourier spectrum. The bit streams obtained with the above described procedures (ALL, MSB, and LSB) are grouped again into m-bit-words and the MPR intensive statistical complexity measure [4] is now eval-

[1] Most (least) significative in the sense of most (least) important. Not to be confuse with the statistical significance.

uated, a quantifier that can be viewed as a functional $C_J[P]$ that characterizes the probability distribution P associated to the time series generated by the dynamical system under study. It quantifies not only randomness but also the presence of correlational structures [2,4,12]. Our intensive SCM is of the form

$$C_J[P] = Q_J[P, P_e] \cdot H_S[P], \tag{1}$$

where, to the probability distribution P, we associate the entropic measure $H_S[P] = S[P]/S_{\max}$, with $S_{\max} = S[P_e]$ ($0 \leqslant H_S \leqslant 1$). P_e is the uniform distribution and S is Shannon's entropy. The disequilibrium Q_J is defined in terms of the extensive Jensen–Shannon divergence [4] and is given by

$$Q_J[P, P_e] = Q_0\big\{S\big[(P + P_e)/2\big] - S[P]/2 - S[P_e]/2\big\}, \tag{2}$$

with Q_0 a normalization constant ($0 \leqslant Q_J \leqslant 1$). Thus, the disequilibrium Q_J is an intensive quantity. For a purely random system, all disequilibrium functional forms would give, strictly, $Q = 0$. But in a quasi-random instance ($Q \to 0$), using a proper distance in probability space is of importance. We remark that the Jensen–Shannon distance is definitely better in this respect than the Euclidean one, as shown in [4].

For evaluating the probability distribution P associated to the time series (dynamical system) under study we follow the methodology proposed by Bandt and Pompe [11] and consider partitions of the d-dimensional space that hopefully "reveal" relevant details of the ordinal-structure of one-dimensional time series. Given the time-series $\{x_t, t = 1, \ldots, T\}$ and an embedding dimension $d > 1$, we are interested in "ordinal patterns" of order d [11,14,15] generated by

$$(s) \mapsto (x_{s-(d-1)}, x_{s-(d-2)}, \ldots, x_{s-1}, x_s), \tag{3}$$

which assign to each time s the d-dimensional vector of values at times $s, s-1, \ldots, s-(d-1)$. Clearly, the greater the d-value, the more information on the past our vectors are able to yield. By the "ordinal pattern" related to the time (s) we mean the permutation $\pi = (r_0, r_1, \ldots, r_{d-1})$ of $(0, 1, \ldots, d-1)$ defined by

$$x_{s-r_{d-1}} \leqslant x_{s-r_{d-2}} \leqslant \cdots \leqslant x_{s-r_1} \leqslant x_{s-r_0}. \tag{4}$$

In order to get a unique result we set $r_i < r_{i-1}$ if $x_{s-r_i} = x_{s-r_{i-1}}$. Thus, for all the $d!$ possible permutations π of order d, the probability distribution $P = \{p(\pi)\}$ is defined by

$$p(\pi) = \frac{\sharp\{s \mid s \leqslant T - d + 1; (s), \texttt{has type } \pi\}}{T - d + 1}. \tag{5}$$

In this expression the symbol $\sharp$ stands for "number". The normalized entropy and the statistical complexity are then evaluated for this "permutation" probability distribution. In the present work we consider $d = 5$.

3. Results

Eight RNG's were analyzed. Three of them—labeled Lorenz, Rössler and Colpitts, respectively,—are of physical origin while the others—Logistic, Cat, Lehmer, Mother and Multiply with Carry (MWC), respectively, are algorithmic ones. Each RNG is converted into a natural-numbers-bit stream using 2^{16} levels ($n = 16$). Each bit stream gives rise to three versions: (a) ALL: keeping all the bits of each 16-bit-word; (b) MSB: picking up only the most significant bit of each word; this binary operation is equivalent to the symbolic dynamics' usual assignment; (c) LSB: picking up only the least significant bit of each word. To ensure that our results are independent of the word length used to process the bit streams, each version was grouped both into 16-bits numbers and 8-bits numbers. Finally, the $C_J[P]$ measure was evaluated. Tables 1 and 2 summarize our results.

In order to computer-studying chaotic systems a suitable discretization procedure must be employed. Its electronic implementation provokes the final decay of the dynamics towards a periodic orbit. In fact, in computers and electronics circuits, we deal only with transient chaos, not with "true" chaos. We made sure that this final decay is towards a periodic orbit of an extremely long period (with regards to the variation of our results according with the total number of words considered). Accordingly, we tested the results' stability as the number of words increases (see Ref. [3]).

Regarding the ALL version $C_J[P]$ value, generators may be grouped into two classes: (1) Those RNG's with $C_J[P] \cong 10^{-4}$: they are Lehmer, Mother, and MWC. These RNG's "pass" the DIEHARD tests and their representative points are uniform clouds without structure in the 3D representation (see Fig. 1a). The MSB and LSB versions are as good as the ALL one for these RNG's. (2) Those RNG's with $C_J[P] \cong 10^{0}$: they are Collpits, Lorenz, Rössler, Logistic, and Cat. For all of them a structure emerges in the 3D representation (see Fig. 1b), which explains the associated higher value of $C_J[P]$. The evaluation of the entropy ($H[P] \cong 1$) is required to guarantee that

Table 1
Intensive SCM of the 5 million 16-bits words sequence

PRNG	ALL	MSB	LSB
Lehmer	0.256100E−04	0.290936E−04	0.276646E−04
Mother	0.277486E−04	0.279572E−04	0.260370E−04
MWC	0.272335E−04	0.238198E−04	0.305736E−04
Lorenz	0.284059E+00	0.365192E+00	0.249695E−04
Collpits	0.282536E+00	0.249920E+00	0.251986E−04
Rössler	0.272253E+00	0.455454E+00	0.256742E−04
Cat	0.325754E−01	0.230632E−04	0.261730E−04
Logistic	0.390117E+00	0.266804E−04	0.250142E−04

Table 2
Intensive SCM of the 10 million 8-bits words sequence

PRNG	ALL	MSB	LSB
Lehmer	0.745106E−04	0.684318E−04	0.717424E−04
Mother	0.680461E−04	0.706939E−04	0.777472E−04
MWC	0.722484E−04	0.632414E−04	0.714218E−04
Lorenz	0.338641E+00	0.290284E+00	0.702518E−04
Collpits	0.357522E+00	0.174460E+00	0.748681E−04
Rössler	0.304973E+00	0.431354E+00	0.690948E−04
Cat	0.100012E−03	0.733130E−04	0.685020E−04
Logistic	0.464910E−01	0.648282E−04	0.667609E−04

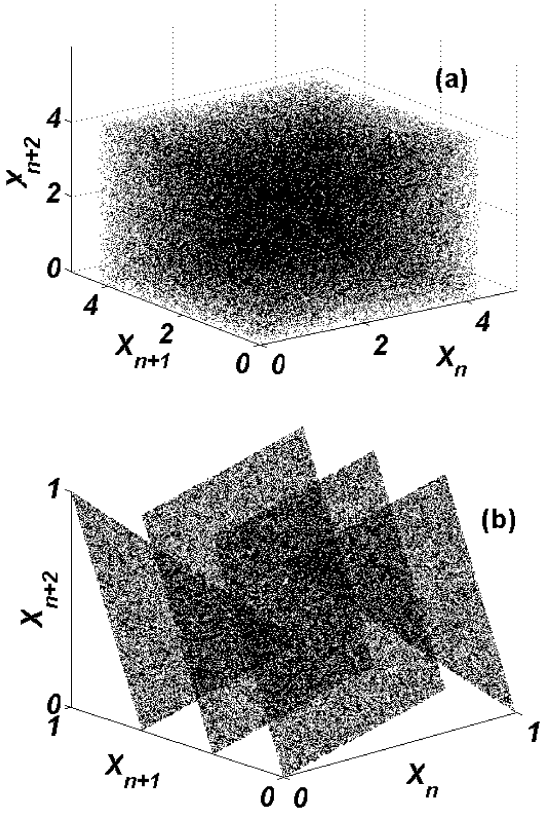

Fig. 1. 3D distribution of: (a) Mother (ALL version, the values have been re-scaled by a factor 10^9); no structure appears. (b) Cat (ALL version); a structure emerges.

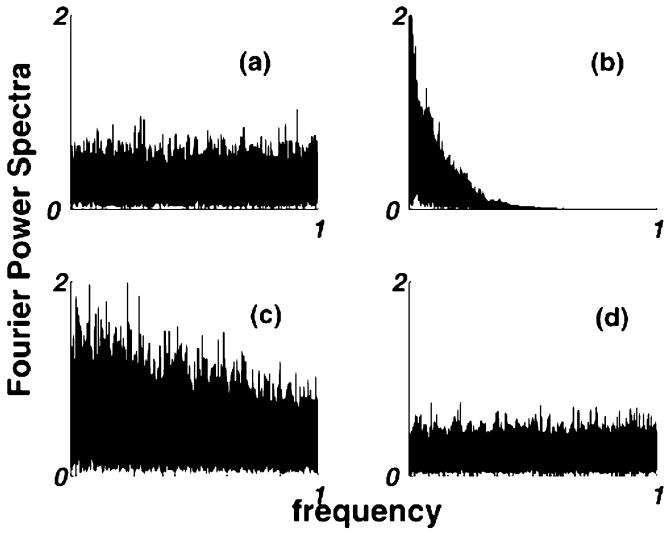

Fig. 2. FFT spectrum of numbers generated sequence by the (a) Logistic: ALL version; Lorenz: (b) ALL, (c) MSB, and (d) LSB versions.

a small $C_J[P]$ corresponds to "randomness". In Tables 3 and 4 we display values for the same cases reported in Tables 1 and 2. All Random Number Generators here studied are improved if the LSB version is used instead of the ALL version. Both the Logistic and the Cat versions are similarly improved if the MSB version is selected.

Table 3
Entropy of the 5 million 16-bits words sequence

PRNG	ALL	MSB	LSB
Lehmer	0.99998929	0.99998780	0.99998843
Mother	0.99998839	0.99998828	0.99998918
MWC	0.99998867	0.99999004	0.99998723
Lorenz	0.31852476	0.43429800	0.99998956
Collpits	0.33250296	0.27427525	0.99998944
Rössler	0.30576186	0.65227355	0.99998925
Cat	0.98628615	0.99999035	0.99998905
Logistic	0.79397578	0.99998884	0.99998951

Table 4
Entropy of the 10 million 8-bits words sequence

PRNG	ALL	MSB	LSB
Lehmer	0.99997204	0.99996951	0.99997034
Mother	0.99997081	0.99997038	0.99997311
MWC	0.99997130	0.99996347	0.99996857
Lorenz	0.83679577	0.33238713	0.99997022
Collpits	0.78620784	0.19095470	0.99997212
Rössler	0.84935722	0.52946970	0.99997004
Cat	0.99996235	0.99996886	0.99996838
Logistic	0.97888955	0.99996753	0.99996904

Notice the following fact. The temporal structure of the "random" series is responsible for the lack of "true" random behavior, as can seen in the spiky-structure of the distribution P. For $d = 5$ there are 5! possible states and some of them will be dominant (see Ref. [16] for an analytical discussion). Consequently, the dynamics is seen to "jump" among different planes of the phase space in a more or less "ordered" fashion, as Fig. 1 clear illustrates.

The reason for this behavior is related to Fourier spectrum's features. This spectrum is almost flat for the Logistic and Cat instances (see the Logistic FFT in Fig. 2a) but it has a low frequency content in the versions Collpits, Lorenz, and Rössler (see the Lorenz FFT in Fig. 2b). Picking up the MSB does not change the spectrum (see Fig. 2c), but by selecting only the LSB we discard the low frequency components, as Fig. 2d adequately exemplifies. Fig. 3 confirms the fact that LSB is a better choice than MSB for the Rössler RNG. Let us stress that all the RNG's with LSB versions do pass the DIEHARD test as well as the suite-one, confirming thereby that an actual improvement has been achieved, on the one hand, and the ability of $C_J[P]$ to *detect* it, on the other one. A complete study of $C_J[P]$ for different kinds of colored noise is in progress and will be published elsewhere. Further work in progress would be that of taking multidimensional CAT maps [17] to ascertain whether our approach is able to detect some kind of structure.

4. Conclusions

Summing up, in this communication we have advanced a prescription to improve, via an adequate randomization scheme, both physical and algorithmic Random Number Generators (RNG's) *that do not pass* Marsaglia's DIEHARD test suite.

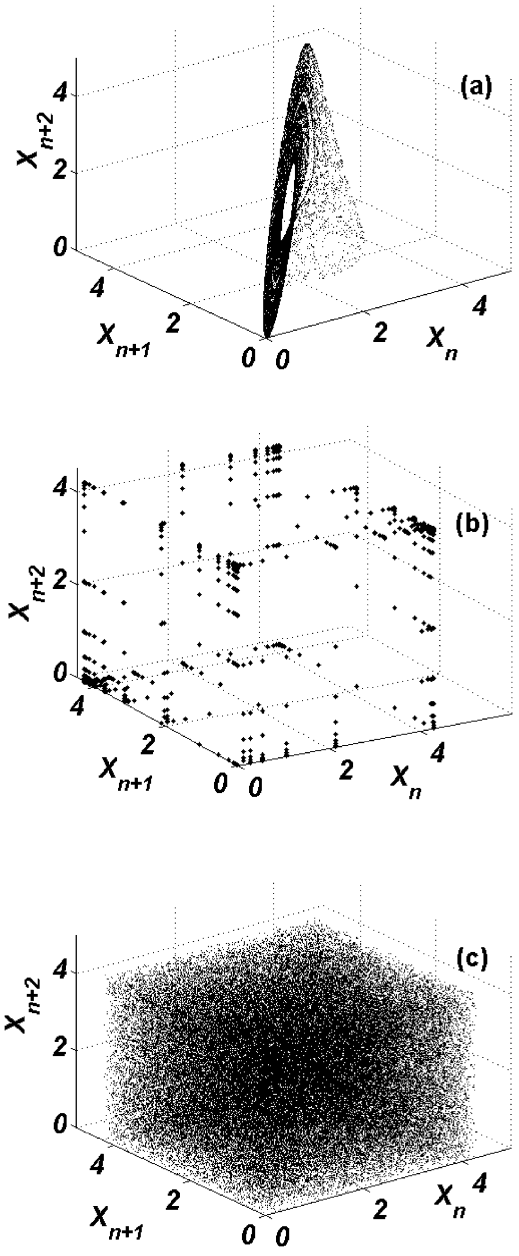

Fig. 3. 3D distribution of Rössler (see Table 2): (a) ALL; (b) MSB, and (c) LSB versions. For (b) and (c) the values have been re-scaled by a factor 10^9.

Additionally, we have shown that a special physical quantifier, based on an intensive statistical complexity measure is perfectly capable of forecasting whether a given RNG is able to successfully face these tests.

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