

Generation of Numbers with the Distribution Close to Uniform with the Use of Chaotic Maps

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Abstract: The method discussed in the paper enables the generation of values from the distribution close to uniform by means of “flattening” continuous distributions of (pseudo-) random sequences of numbers. The method makes use of chaotic maps with uniform distribution. The set of initial conditions for such recursive functions consists of any sequences of numbers derived in a (pseudo-) random manner. Thanks to an appropriate quantity of the iterations of such chaotic maps, the initial conditions set is reduced to the sequence of numbers with the distribution close to uniform. The method may be employed for the derivation of (pseudo-) random values using for example: sets of physical measurements, values of stock exchange indices or biometrics data like EEG signals. Consequently, the obtained values may be applied in simulations or in cryptography.

1 INTRODUCTION

Sequences of numbers derived from uniform distribution are of fundamental importance in many fields of science, for example: in cryptography or in simulations.

In cryptography, the sequences derived in a (pseudo-) random manner give grounds for many ciphers, called *stream ciphers*. Such ciphers use binary (pseudo-) random sequences for encryption of each bit of a given message by means of, i.e. XOR function. When such binary sequences are obtained in a random manner and additionally other conditions are fulfilled, the ciphering method is proven to be unbreakable (Stallings, 2011). An easy way to obtain truly random numbers is through physical measurements, i.e. atmospheric noise (Random.org, 2014) or chaotic oscillator (Ergün and Özogüz, 2007), although those generators not always have uniform distribution (Ergün and Özogüz, 2007).

In simulations, the sequences of numbers from the uniform distribution are used, for example, in the Monte-Carlo method (Metropolis and Ulam, 1949), which enables the modelling of very complex physical processes (Binder and Heerman, 2010), financial processes (Boyle, 1977) and others.

The sequences of numbers derived from the uniform distribution are also used as basic tools for the generation of numbers from other types of distribution, for example – from the normal distribution. Such

sequences may be derived by means of inverse cumulative distribution function (Devroye, 1986) or transformations, for example, the Box-Muller transformation (Box and Muller, 1958) for the normal distribution.

To derive pseudo-random numbers from the uniform distribution algorithms called Pseudo-Random Numbers Generators (PRNGs) are used (Blum et al., 1986; Matsumoto and Nishimura, 1998; Ziff, 1998). Implementations of such algorithms may be encountered in any programming language in the form of ready-made functions (modules) which facilitate easy generation, for example: *rand()* in C language or *random()* from the *random* module in python.

The method presented within the scope of this paper makes it possible to obtain numbers with the uniform distribution by means of chaotic maps. The distribution of the iterative variable of such maps must be uniform. The set of the initial conditions for such recursive function consists of any sequences of numbers derived in a (pseudo-) random manner, for example, stock exchange indices data or biometric data like EEG signals (Chen, 2014). By means of an appropriate number of iterations the set shall be reduced to a sequence of numbers with the distribution close to uniform.

On the other hand an easy method of reducing the sequence with any distribution to the sequence of uniform distribution is the transformation of the output sequence with the use of its cumulative distribution

function. If the sequence of the numbers is derived from, for example, stock exchange data or EEG signals, this is impossible.

2 CHAOTIC MAPS WITH UNIFORM DISTRIBUTION

The most popular chaotic map with uniform distribution widely discussed in scientific publications is the so called *skew tent map* defined by the following equation:

$$x_{k+1} = \begin{cases} \frac{x_k}{p}, & x_k \in [0, p) \\ \frac{1-x_k}{1-p}, & x_k \in [p, 1] \end{cases} \quad (1)$$

where $p \in (0, 1)$. For each value of parameter p the skew tent map is chaotic and the distribution of its iterative variable is uniform. For $p = 0.5$ the recursion (1) is called *tent map*.

Another chaotic maps with uniform distribution are discussed in (Anikin at al., 2008).

The density function $\rho(x)$ of recursive functions like (1) may be obtained by solving the Frobenius–Perron equation given by the formula (Ott, 1993):

$$\rho(x) = \int \rho(y) \delta[x - M(y)] dy, \quad (2)$$

where $\delta(x)$ is a *delta function* and $M(x)$ is a recursive function. However, the solution of this equation is usually impossible. Hence, the following method is used, as it designates, in a numerical manner, the distribution of an iterative variable. The whole range of variable x is divided into N equal sub-ranges. For each of the sub-ranges, the quantity of the numbers that fell into it in the course of the iteration of the recurrence is calculated. The values are successively denoted as n_1, n_2, \dots, n_N . In the next step the values of $\frac{n_1}{N\Delta x}, \frac{n_2}{N\Delta x}, \dots, \frac{n_N}{N\Delta x}$ are designated, where Δx denotes the length of the sub-range. The continuous graph plotted for the couples of points $\left\{ i \Delta x, \frac{n_i}{N\Delta x} \right\}$ approximates the density function of the recursive function.

An exemplary distribution numerically derived for the skew tent map is shown in Figure 1.

The above numerical method was also used to obtain density functions in presented in this paper examples.

3 THE METHOD

Let $T^n(x)$ denote the n -th iteration of the chaotic map with uniform distribution started at initial condition

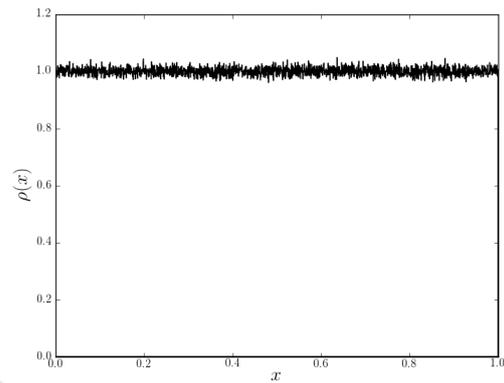


Figure 1: The distribution derived numerically for skew tent map with $p = 0.45$.

x . Furthermore, let $X = \{x_0, x_1, \dots, x_M\}$ be a certain (pseudo-)random sequence with any (even unknown) distribution. In such case, the sequence of the numbers:

$$U = \{u_0, u_1, \dots, u_M\} \quad (3)$$

where $u_i = T^n(|ax_i|)$ for $i = 0, 1, \dots, M$ and a is a normalization coefficient, for an appropriate quantity of iterations n has the distribution close to uniform.

4 EXAMPLES

4.1 Sequence of Pseudo-random Numbers with Normal Distribution

The sequences of numbers with standard normal distribution were derived with the use of *gauss()* function of module *random* in language *python*. By applying the discussed method with the skew tent map with $p = 0.45$ to the sequences, the successive distributions were obtained as shown in Figure 2. Furthermore, as seen in Figure 2, for only $n = 4$, the distribution of the derived sequence approximates the uniform distribution. In Figure 3 dependence (u_k, u_{k+1}) between the successive elements of the sequence (3) was shown in a graphic manner. It may be observed that the obtained values evenly and without noticeable dependencies cover the unit square.

4.2 Sequence of Numbers Derived from the Logistic Map

The logistic map is described by the equation:

$$x_{k+1} = rx_k(1 - x_k) \quad (4)$$

where $r \in [0, 4]$. For parameter $r = 4$ the density function $\rho(x)$ of (4) is equal to (Lasota and Mackey, 1994):

$$\rho(x) = \frac{1}{\pi\sqrt{x(1-x)}} \tag{5}$$

The graph in Figure 4 presents the density function (5) obtained in a numerical manner. By means of the discussed method, basic distributions shown in the consecutive graphs in Figure 4 were plotted, whereas, in Figure 5 dependence (u_k, u_{k+1}) between the successive elements of the derived sequence (3) was shown. For $n = 13$ the obtained values evenly and without noticeable dependencies cover the unit square.

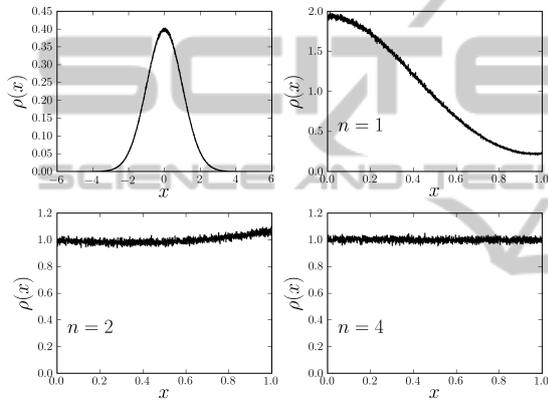


Figure 2: The derived distributions of the sequence of numbers transformed by means of the discussed method with the skew tent map with $p = 0.45$ for the successive values of $n = 1, 2, 4$. The flattening of the standard normal distribution to the uniform distribution may be observed in the successive graphs.

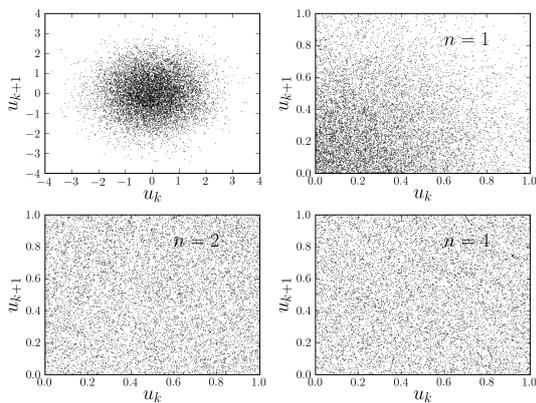


Figure 3: Graphic representation of the dependence of the couples of numbers (u_k, u_{k+1}) derived from the sequences in Figure 2.

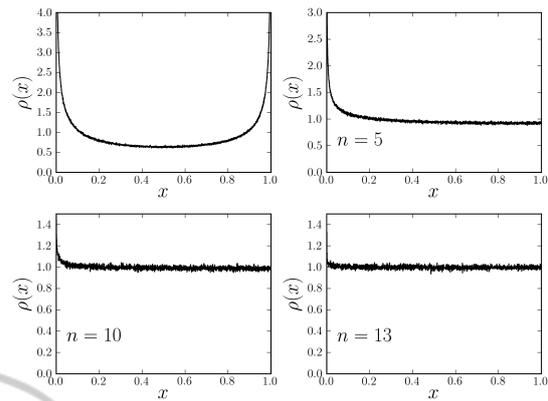


Figure 4: The derived distributions of the sequence of numbers derived from (4) and transformed by means of the discussed method with the skew tent map with $p = 0.45$ for the values of $n = 5, 10, 13$. The flattening of distribution (5) to the uniform distribution may be observed.

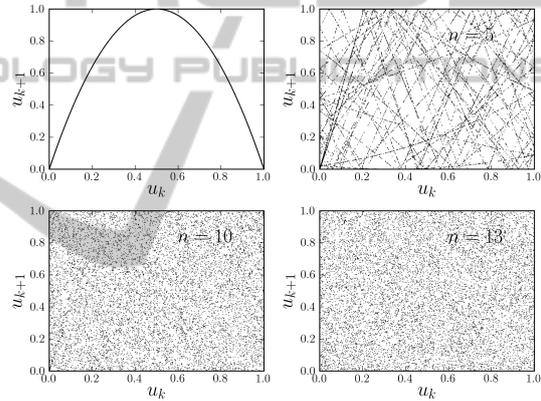


Figure 5: Graphic representation of the dependence of the couples of numbers (u_k, u_{k+1}) derived from the sequences in Figure 4.

4.3 Japan / U.S. Foreign Exchange Rate Time Series

Financial time series like stock exchange indices values are a large data sets, that can be potentially used to generate pseudo-random numbers. Such time series have a fractal nature, i.e. while looking at a particular time series it is impossible to state whether it shows the relation in the successive years or at a given day (Mandelbrot and Hudson, 2004). Hence, such type of numerical data may be used as a set of the initial conditions for the discussed method. As an example the numerical data from (FRED Economic Data, 2014) that represents the daily relation between the Japanese Yen and the USA dollar in the time range starting with January 4th 1971 are analyzed.

The graph of the time series of the analyzed data

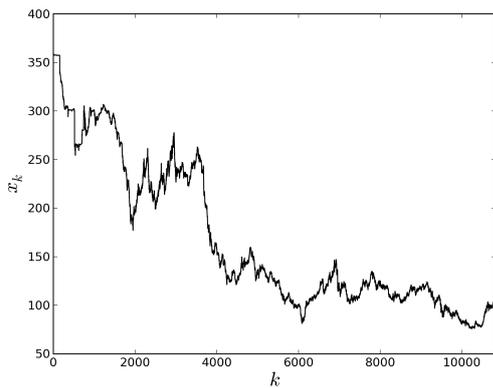


Figure 6: Numerical data describing the relation between the Japanese Yen and the USA dollar (FRED Economic Data, 2014).

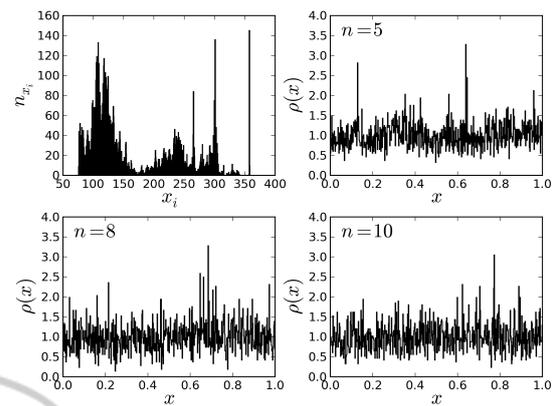


Figure 8: Histogram of the numerical data of the time series (FRED Economic Data, 2014) and the distributions derived by means of the discussed method with the skew tent map with $p = 0.45$ for $n = 5, 8, 10$.

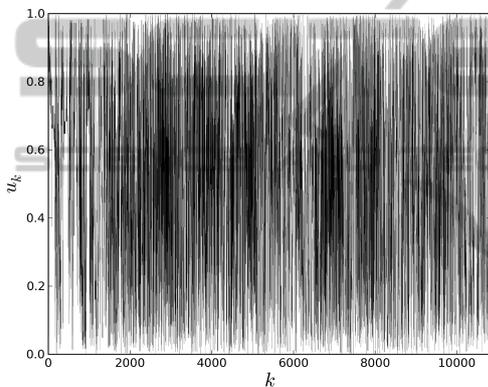


Figure 7: Time series derived from the sequences in Figure 6 using discussed method with the skew tent map with $p = 0.45$ for $n = 10$.

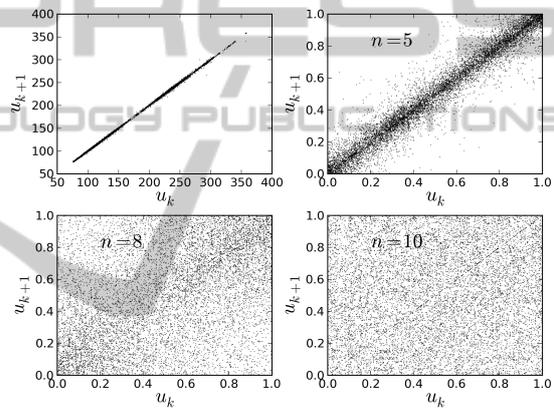


Figure 9: Graphic representation of the dependence of the couples of numbers (u_k, u_{k+1}) derived from the sequences in Figure 8.

is presented in Figure 6, whereas, in Figure 7 the obtained time series using the discussed method with the skew tent map with $p = 0.45$ for $n = 10$ is shown. In Figure 8 the histogram of the data and successive distributions of the iterative variable derived for $n = 5, 8, 10$ are illustrated. As inferred from the graph, the successive distributions approximate the uniform distribution. Dependence (u_k, u_{k+1}) between the successive values of the analyzed data is shown in Figure 9. For $n = 10$ the values cover the unit square evenly and without noticeable dependencies.

5 CONCLUSIONS

The discussed method enables the generation of numbers from the distribution that approximates the uniform distribution. The method makes use of chaotic maps with uniform distribution. The set of the initial conditions for the recursive functions may be as-

sumed as any sequence of (pseudo-) random numbers. In the course of an appropriate quantity of iterations, the set may be reduced to the sequence of numbers with the distribution approximating the uniform one. The method may be applied for generating (pseudo-) random numbers with the uniform distribution from a given source, if its distribution is not flat. Such source may be constituted by, for example, a set of data derived from physical measurements, values of stock exchange indices or biometric data like EEG signals. The sequences generated by means of the method may be useful for simulations or cryptography. Furthermore, the method is very simple for practical application.

REFERENCES

- Anikin, V.M., Arkadasky, S.S., Kuptsov, S.N., Remizov, A.S., Vasilenko, L.P., 2008. Lyapunov exponent for chaotic 1D maps with uniform invariant distribution. *Bulletin of the Russian Academy of Sciences: Physics*, 72(12):1684–1688.
- Binder, K., Heermann, D.W., 2010. *Monte Carlo Simulation in Statistical Physics. An Introduction*, Springer, Berlin 5th edition.
- Blum, L., Blum, M., Shub, M., 1986. A Simple Unpredictable Pseudo-Random Number Generator. *SIAM Journal on Computing*, 15(2):364–383.
- Boyle, P.P., 1977. Options: A Monte Carlo approach. *Journal of Financial Economics*, 4(3):323–338.
- Box, G.E.P., Muller, M.E., 1958. A Note on the Generation of Random Normal Deviates. *The Annals of Mathematical Statistics*, 29(2):610–611.
- Chen, G., 2014. Are electroencephalogram (EEG) signals pseudo-random number generators? *Journal of Computational and Applied Mathematics*, 268:1–4.
- Ergün, S., Özogüz, S., 2007. Truly random number generators based on a non-autonomous chaotic oscillator. *AEU - International Journal of Electronics and Communications*, 61(4):235–242.
- FRED Economic Data (2014). Japan / U.S. Foreign Exchange Rate. <http://research.stlouisfed.org>
- Devroye, L., 1986. *Non-Uniform Random Variate Generation*, Springer, New York 1st edition.
- Dorfman, J.R., 1999. *Cambridge Lecture Notes in Physics: An introduction to chaos in nonequilibrium statistical mechanics, volume 14*, Cambridge University Press.
- Lasota, A., Mackey, M.C., 1994. *Chaos, Fractals, and Noise: Stochastic Aspects of Dynamics*, Springer, New York 2nd edition.
- Mandelbrot, B., Hudson, R.L., 2004. *The Misbehavior of Markets: A Fractal View of Financial Turbulence*, Basic Books.
- Matsumoto, M., Nishimura, T., 1998. Mersenne twister: a 623-dimensionally equidistributed uniform pseudo-random number generator. *ACM Transactions on Modeling and Computer Simulation*, 8(1):3–30.
- Metropolis, N., Ulam, S., 1949. The Monte Carlo Method. *Journal of the American Statistical Association*, 44(247):335–341.
- Ott, E., 1993. *Chaos In Dynamical System*, Cambridge University Press.
- Truly random numbers (2014). <http://www.random.org/>
- Stallings W., 2011. *Cryptography and Network Security: Principles and Practice*, Pearson Education, 5th edition.
- Ziff, R.M., 1998. Four-tap shift-register-sequence random-number generators. *Computers in Physics*, 12(4):385–392.