CRYPTOGRAPHIC ANALYSIS OF RANDOM

SEQUENCES

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Chapter Page	•
I. INTRODUCTION	
1.1 Random Numbers and Random Sequences11.2 Types of Random Number Generators21.3 Random Number Generation Methods31.4 Applications of Random Numbers51.5 Statistical tests of Random Number Generators7	
II. COMPARISION OF SOME RANDOM SEQUENCES9	
2.1 Binary Decimal Sequences92.1.1 Properties of Decimal Sequences10• Frequency characteristics10• Distance Properties13• Randomness Properties14• Autocorrelation Properties142.1.2 Generation of Decimal Sequences152.1.3 Examples of Decimal Sequences162.1.4 Randomness Measured by Autocorrelation function202.2 Binary sequences from windows PC20	
III. MESH ARRAY SCRAMBLING OF NUMBERS	
3.1 Standard and Mesh Arrays233.2 Matrix Multiplication on a Mesh Array243.3 Scrambling Transformations263.3.1 Generating Cycles283.3.2 Prime Periods293.4 Generating Binary Sequence30	
IV. CRYPTOGRAPHIC HARDENING OF PSEUDORANDOM SEQUENCES32	
4.1 The PR(n) Sequence324.2 PR(n) sequences from Windows PC414.3 Mesh PR(n) Sequence414.4 Nested PR(n) Sequences42	

TABLE OF CONTENTS

Chapter	Page
V. CONCLUSION	44
REFERENCES	45

LIST OF TABLES

Table

Page

4.1. Reduction in the largest value Autocorrelation function values for 1541	
4.2. Reduction in the largest value Autocorrelation function values for 1907	
4.3. Reduction in the largest value Autocorrelation function values for 2243	
4.4. Reduction in the largest value Autocorrelation function values for 2333	40
4.5. Reduction in the largest value Autocorrelation function values for 2843	40
4.6. The largest value autocorrelation values for Windows RNG	41
4.7. The largest value autocorrelation values for the mesh array sequence	41
4.8. Nested values for windows RNG	42
4.9. PR(n) values for all the sequences	43

LIST OF FIGURES

Figure

Page

2.1. General Random sequences as a subset of d-sequences	9
2.2. Autocorrelation for binary sequence generated using p=1117	17
2.3. Autocorrelation for binary sequence generated using p=1541	18
2.4. Autocorrelation for binary sequence generated using p=1861	19
2.5. Autocorrelation for binary sequence generated from windows PC	22
3.1. Standard Array matrix multiplication of two 3×3 matrices	24
3.2. Mesh Array matrix multiplication of two 4×4 matrices C = AB	25
3.3. Mesh Array matrix multiplication of matrix A with Identity Matrix	27
3.4. Autocorrelation Function of periods of mesh array	31
4.1. Autocorrelation function for PR(1) for 1/1571	33
4.2. Autocorrelation function for PR(3) for 1/1571	34
4.3. Autocorrelation function for PR(5) for 1/1571	35
4.4. Autocorrelation function for PR(7) for 1/1571	36
4.5. Autocorrelation function for PR(9) for 1/1571	37
4.6. Autocorrelation function for PR(11) for 1/1571	38

CHAPTER I

INTRODUCTION

1.1 Random Numbers and Random Sequences:

A random number is a number generated by some process so that the outcome is unpredictable. It is one number that can be drawn from a set of possible numbers, each of which is equally probable (in case of single numbers).

When each number drawn from a set of numbers is statistically independent of the others then that sequence is said to be random sequence. Sometimes it is difficult to find whether the sequence is random or not. Many investigators have proposed definitions to characterize these random number sequences for overcoming the difficulties arising from the same. According to Knuth[1], "Random sequence is a sequence of independent numbers with a specified distribution and a specified probability of falling in any given range of values". Scheneier[2] defined that "A sequence of random numbers is a sequence that has the same statistical properties as random bits, is unpredictable and cannot be reliably reproduced".

There are several types of random sequences of which algorithmically random and pseudo random sequences are most important for our purposes. *Algorithmically random sequence*[3] is a sequence of an infinite sequence of binary digits which appear random to any algorithm. *Pseudo random sequences*[3] are those that typically exhibit statistical randomness in spite of being generated by an entirely deterministic casual process. This process not only makes it easier to produce but also helps in testing and fixation of software.

Some examples for binary random number sequences are as follows:

- 01101010000010011110011
- 11011110011101011111011

On the examination of the above sequences, the second and third sequences appear random while the first one does not. From a frequency point of view each of these sequences is equally random, while from an algorithmic point of view the first one is clearly non-random. Random numbers are used for various purposes like generating data encryption and decryption keys, e-commerce, simulating and modeling of complex phenomena and selecting random samples from larger data sets. They also have applications in the arts including literature, music, games and even gambling.

Random numbers that are generated by computers are pseudo-random numbers[3]. True random numbers[3] are numbers which are completely independent of the other numbers in the sequence and where the output is inherently unpredictable.

In a recent article, Anthes [4] summarizes results on generating true random numbers. In particular, he mentions the work at Intel Corp. to use thermal noise on the central processing unit of the computer as random number generator (RNG) [5]. This is not unlike the RNGs based on quantum processes that have been proposed elsewhere [6], but quantum processes come with their own uncertainty [7]-[10].

Randomness is generally measured in terms of probability or of complexity. From the lens of probability, all binary sequences of length n are equivalent. From the point of view of complexity, it depends on the algorithm that has been used to generate the sequence. Ritter has provided a summary of several measures of algorithmic complexity [11].

1.2 Types of Random Number Generators:

Given their many applications the need for a fast generation of random sequences using a computer program is essential. Two approaches have been developed for generating random

sequences using a computer program: Pseudo-Random Number Generators (PRNGs) and True Random Number Generators (TRNGs)[14].

PRNGs[14] are generators which uses algorithms that have mathematical formulae or just precalculated tables to produce random number sequences. Linear congruential method is one of the good example for PRNGs. PRNGs are efficient when they can produce many numbers in a short time. Modern PRNGs have a period that is so long that it can be ignored for most practical purposes.

TRNGs[14] are used to extract the randomness from the physical phenomena and introduce it into the computer. The best way to generate a TRNG is using quantum processes. Another method is to use is a radioactive source that is fed into the computer avoiding any buffering mechanisms in the operating system.

1.3 Random Number Generation Methods:

Traditionally, the first method used to generating random numbers by computer was Von Neumann's mid-square method[15]. The idea behind this method was to take the square of previous random number and extract the middle digits. But the mid-square method was slow and unsatisfactory. To overcome with this drawback, congruential methods were introduced which give better results.

Generally, an acceptable sequence of pseudo random numbers should satisfy the following properties:

- 1. Uniformly distributed
- 2. Statistically independent
- 3. Reproducible and

4. Non-repeating for any desired length

Composite generators[15] combine two separate conguential generators. By combining two separated generators, we can achieve better statistical behavior than separate generators. Here the composite generators uses the second congruential generator to shuffle the output of first congruential generator. The first generator is used to fill a vector with the first k random numbers of size n where as the second generator is used to generate a random integer r which is uniformly distributed over the numbers 1, 2, ..., k. The random number which is stored in the rth position is returned as the first random number and then replaces the random number in rth position with a new random number. This process repeats and generates a random sequence.

Tausworthe generators[15] are additive congruential generators which are obtained when the modulus m is equal to 2.

The formula for these generators is:

$$\mathbf{x}_{i} = (a_{1}\mathbf{x}_{i-1} + a_{2}\mathbf{x}_{i-2} + a_{n}\mathbf{x}_{i-n}) \pmod{2}$$

where x_i can be either 0 or 1. These generators are independent of the computer used and its word size and also have very large cycles and even produce a stream of bits. Two or more Tausworthe generators can be combined in order to obtain statistically good output.

This is a newer algorithm[15] whose output has very excellent statistical properties when compared to other generators and its period is very long i.e., 2^{19937} -1. This algorithm used 19937 bits long seed value on a very large linear feedback shift register.

1.4 Applications of Random Numbers:

Random numbers has many applications in several fields:

- Monte Carlo simulation method
- Spectrum spreading telecommunication systems
- Generation of primes
- Cryptography
- Computer games and Gambling

A Monte Carlo Method[16] is a technique which uses random numbers and probability to solve problems. It is mainly used when the model is complex, non linear, or has more uncertain parameters. Typically a simulation involves over 10,000 evaluations of a model.

In spread-spectrum[17] random numbers are used in order to generate the signals to spread in the frequency domain.

Random numbers are also used for generation of prime numbers. Random primes are used in RSA encryption. These numbers are uniformly distributed only on the primes in the range but not on the entire range because primes are not uniformly distributed over ranges of positive integers.

In cryptography, random numbers are used for generation of the following[17]:

- *Nonce* is an abbreviation of number used once. It is often a random or pseudo-random number generated from an authentication protocol which is used to avoid replay attacks.
- *Key* is a piece of information or a parameter which determines the functional output of an algorithm. In encryption, a key transforms plain text into cipher text and cipher text into plain text in decryption. Keys are also used in other cryptographic algorithms such

as digital signature schemes and message authentication codes. Without a key, the algorithm would not produce useful result.

- *Challenge* is a protocol where in one party presents a question (challenge) and another party must provide a valid answer (response) to be authenticated. An example for challenge-response protocol is password authentication where the challenge is asking for the password and the valid response is the correct password.
- *Initialization vector* is a fixed size input to a cryptographic primitive that should be random or pseudorandom. Some cryptographic primitives require initialization vector only to be non-repeating where the required randomness is derived internally.
- *Padding byte* is nothing but padding the input with the padding string of between 1 and 8 bytes to make the total length a multiple of 8 bytes. The value of each byte of the padding string is set to the number of bytes added i.e. 8 bytes of value 0x08, 7 bytes of value 0x07, 2 bytes of 0x02, or one byte of value 0x01.
- *Blind Signature* can be implemented by using a number of public key signing schemes, like RSA and DSA. In blind signature, the message is first blinded by combining it with a random blinding factor. The blinded message is passed to a signer, and then the signer signs it using a standard signing algorithm. The resulting message, along with the blinding factor, can be verified against the signer's public key.

Random numbers plays a vital role in casinos and, in turn, entertainment[18]:

- Role playing games used to select the roles randomly.
- Card shuffling used for shuffling cards randomly.
- Lottery tickets used to obtain random numbers for the tickets.
- Indoor tennis game used for making new combination of players.
- Dungeons and Dragons based on the random rolls of dice.

Random graphs[19] are one of the mainstays of modern discrete mathematics. They have been employed extensively as models of real world networks of various types and in epidemiology.

1.5 Statistical tests for Random Number Generators:

The Diehard tests[20] are the statistical tests which are used for measuring the quality of a random number generator. These tests require input as a specially formatted binary file containing 3 million 32-bit integers. After producing this specially formatted binary file, Diehard tests are performed on the resulting file. The tests are:

- *Overlapping permutations:* Analyze sequences of five consecutive random numbers. The 120 possible orderings should occur with statistically equal probability.
- *Birthday Spacings:* Choose random points on a large interval. The spacings between the points should be asymptotically exponentially distributed. The name is based on the birthday paradox.
- *Monkey Tests:* Treat sequences of some number of bits as "words". Count the overlapping words in a stream. The number of "words" that don't appear should follow a known distribution. The name is based on the infinite monkey theorem.
- *Ranks Of Matrices:* Select some number of bits from some number of random numbers to form a matrix over {0,1}, then determine the rank of the matrix. Count the ranks.

- *Parking Lot Test:* Randomly place unit circles in a 100 x 100 square. If the circle overlaps an existing one, try again. After 12,000 tries, the number of successfully "parked" circles should follow a certain normal distribution.
- *Count The 1s:* Count the 1 bits in each of either successive or chosen bytes. Convert the counts to "letters", and count the occurrences of five-letter "words".
- *Minimum Distance Test:* Randomly place 8,000 points in a 10,000 x 10,000 square, then find the minimum distance between the pairs. The square of this distance should be exponentially distributed with a certain mean.
- *Random Spheres Test:* Randomly choose 4,000 points in a cube of edge 1,000. Center a sphere on each point, whose radius is the minimum distance to another point. The smallest sphere's volume should be exponentially distributed with a certain mean.
- *The Squeeze Test:* Multiply 2³¹ by random floats on [0,1) until you reach 1. Repeat this 100,000 times. The number of floats needed to reach 1 should follow a certain distribution.
- *Runs Test:* Generate a long sequence of random floats on [0,1). Count ascending and descending runs. The counts should follow a certain distribution.
- *Overlapping Sums Test:* Generate a long sequence of random floats on [0,1). Add sequences of 100 consecutive floats. The sums should be normally distributed with characteristic mean and sigma.
- *The Craps Test:* Play 200,000 games of craps, counting the wins and the number of throws per game. Each count should follow a certain distribution.

CHAPTER II

COMPARISION OF SOME RANDOM SEQUENCES

2.1 Binary Decimal Sequences:

Binary random sequences[21] are generated by starting with the decimal sequences. A decimal sequence is obtained by representing a number in a decimal form in a base r and it may terminate, repeat or be aperiodic. For a certain class of decimal sequences of 1/q, q prime, the digits spaced half a period apart add up to r-1, where r is the base in which the sequence is expressed. These decimal sequences are periodic and their randomness properties are checked only in one period. Decimal sequences are known to have good auto correlation properties and they can be used in applications involving pseudorandom sequences.

Any periodic sequence can be represented as a generalized d-sequence m/n, where m and n are suitable natural numbers, i.e., positive integers.



Figure 2.1: General Random sequences as a subset of d-sequences

2.1.1 Properties of Decimal Sequences:

Properties of decimal sequences from [22] to [24], which are summarized below:

Frequency Characteristics:

Theorem 1: Any positive number x may be expressed as a decimal in the scale of r

$$A_1A_2...A_{s+1}.a1.a2...$$

Where $0 \le A_i < r$, $0 \le a_i < r$, not all A and a are zero, and an infinity of the a_i are less than (r-1). There is a one to one correspondence between the numbers and the decimals, and

$$X = A_1 r^s + A_2 r^{s-1} + \ldots + A_{s+1} + a_1/r + a_2/r^2 + \ldots$$

For example, ¹/₄ can be represented as 0.25 in the scale of 10 and 0.01 in the scale of 2. The decimal sequences of rational and irrational numbers may be possibly used to generate pseudorandom sequences and this is suggested by the following properties of decimals of real numbers.

Theorem 2: Almost all decimals, in any scale, contain all possible digits which mean that the property applies everywhere except to a set of measure zero.

Theorem 3: Almost all decimals, in any base, contain all possible sequences of any number of digits.

Theorem 2 and 3 guarantee that a decimal sequence missing any digit is exceptional to know the behavior of the digits for any particular decimal sequence.

For example: A number x is said to be simply normal in base r if in the decimal of x each of the r possible digits occur with a frequency 1/r, i.e.,

$$\text{Lim}_{h} / n \rightarrow 1/r$$
 where $n \rightarrow \infty$

For all b, where the digit b occurs n_b times in the first n places.

Theorem 4: Almost all numbers are normal in any base.

It may be noted, however, that while finite periodic decimal sequences may be simply normal in a given scale, they will not be simply normal in all scales. For example, consider

$$x = 0.0123456789$$

which is simply normal in the scale of 10. In the scale of 1010 the same number is x = .b where b is 123456789, which is not simply normal, 1010-1 digits being missing. So, a normal number cannot be rational. Theorem 4 guarantees the existence of an uncountably infinity of irrational numbers, whose decimal representation would perfectly exhibit all randomness properties. Generating a periodic sequence from its rational number representation is computationally less complex than generating it from an irrational number.

Theorem 5: The decimal for a rational number p/q between 0 and 1 is terminating or recurring, and any terminating and recurring decimal in the scale of 10 is equal to a rational number. If (p,q)=1, $q=2^{\alpha}5^{\beta}$, and $\max(\alpha,\beta) = \mu$, then the decimal terminates after μ digits. If p,q)=1, $q=2^{\alpha}5^{\beta}Q$, where Q > 1, (Q,10) = 1, and v is the order of 10(mod q), then the decimal contains μ nonrecurring and v recurring digits. **Theorem 6:** Suppose 0 < x < 1, x = p/q,(p,q) = 1. If $q = s^{\alpha}t^{\beta}...u^{\gamma}$, where s,t...u are the prime factors of r, and $\mu = \max(\alpha, \beta...\gamma)$, then the decimal for x terminates at the μ th digit. If q is prime to r and v is the order of r(mod q), then the decimal is pure recurring and has period of v digits. If $q = s^{\alpha}t^{\beta}...u^{\gamma}Q$, (Q>1), Q is prime to r, and v is the order of r(mod Q), then the decimal is mixed recurring, and has μ non-recurring and v recurring digits.

Theorem 7: A maximum length decimal sequence when multiplied by p, p < q, is a cyclic permutation of itself.

The remainders 1,2,...q-1 obtained during the division of 1/q have a one-way correspondence with the coefficients 0,1,...r-1. Since p/q starts off with a remainder rp(mod q) instead of r(mod q), there would be a corresponding shift of a decimal sequence.

Theorem 8: if the decimal sequence, in the scale of r, of p/q; (p,q)=1, p < q, and (r,p) = 1 is shifted to the left in a cyclic manner, 1 times, the resulting sequence corresponds to the number $p^{1/q},(p^{1},q)=1,p^{1}< q$ where $p^{1} = r^{1} \times p \pmod{q}$.

Theorem 9: For a maximum length decimal sequence $1/q = a_1a_2...a_k$, k = q-1, in the scale of r:

 $a_i + a_{k/2+I} = r-1$

For example: $x = \{1/19\}$ in base r = 2

 $x \leftrightarrow 0\ 0\ 0\ 0\ 1\ 1\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 0\ 0\ 1\ 0\ 1$

Here, $a_i + a_{k/2+I} = r-1=1$

The extension to the above theorem is stated below.

Theorem 10: If the period k of the decimal sequence of 1/q, q prime, is even in the scale r: $a_i + a_{k/2+I} = r-1$ Some additional structural properties of the remainder and the decimal sequences digits are presented below.

Theorem 11: For a maximal length decimal sequence the remainder sequence $m_1m_1...m_k$, k = q-1, satisfies the relations

 $m_i m_{q-1} = m_1 \pmod{q}$

 $m_i m_{l-i} - 2 m_i m_{l-j} + m_l = 0 \pmod{q}$ for all I, j, l.

Theorem 12: The decimal sequence of 1/q, where q is of the form $r^N + 1$ when expressed in the scale of r would be N consecutive zeros followed by N consecutive (r-1)'s.

Distance Properties:

Let the ith remainder in the division of 1/q be represented by m_i , where $m_0 = 1$, $m_i = r m_{i-1} - qa_i$. So, the following is obtained.

$$m_{i+j} = r^{j+1}m_{i-1} - ql_i(j+1)$$

where $l_i(j+1) = r^j a_i + r^{j-1} a_{i+1} + \ldots + r a_{i+j-1} + a_{i+j}$.

Theorem 13: For a binary decimal sequence 1/q, if $2^m > q$, then all l_i (m) are different.

For such a sequence, all subsequences of length m are different.

Theorem 14: The Hamming Distance d_j between the binary maximum length sequence $\{1/q\}$ and its jth cyclic shift satisfies

$$d_j \ge k/m, j \ne 0, j < k,$$

where $2^{m} > q$, k = q-1.

At least one of each m consecutive digits is different from Theorem 13. Hence, the minimum distance between each set of m digits is one. For a total of k such group of digits, the distance is k, and since the sequence considered is m times over, the distance is k/m.

Randomness Properties:

The randomness of a periodic binary sequence of +1's and -1's can be checked by comparing the run characteristics of +1's and -1's as well as its autocorrelation function to that obtained for a normal number where the digits are independent.

Autocorrelation Properties:

Let the equation below represent the auto-correlation function of the decimal sequence $a_1...a_n$.

$$C(k) = \frac{1}{n} \sum_{j=0}^{n} a_j a_{j+k}$$

For a normal number, the autocorrelation function is:

$$\mathbf{C}_1(\tau) = \mathbf{E}(\mathbf{a}_n \mathbf{a}_{n+\tau})$$

Where the nth digit of the sequence $a_n \square \{0,1,2, \dots r-1\}$. The autocorrelation function is two-valued for a binary random sequence.

2.1.2 Generation of Decimal Sequences:

According to the standard method, the binary d-sequence is generated using the algorithm below[16]:

 $a(i) = 2^i \mod p \mod 2$

where p is a prime number. The maximum length period (p-1) sequences are generated when 2 is a primitive root of p.

This may be rewritten as:

$$a(0)=2$$

$$b(i+1) = 2b(i) \mod q$$

$$a(i)=b(i) \mod 2$$

To generate decimal expansions of 1/p, one may use the following formula[17]:

If prime ends in 1,

$$a(i) = 9 \times 10^{i} \mod p \mod 10$$

If prime ends in 3,

$$a(i) = 3 \times 10^i \bmod p \mod 10$$

If prime ends in 7,

$$a(i) = 7 \times 10^i \text{ mod } p \text{ mod } 10$$

If prime ends in 9,

$$a(i) = 10^i \mod p \mod 10$$

The above formula produces a random sequence of decimal numbers ranging from 0 to 9. These decimals are then converted to an equivalent binary numbers, which results in a sequence of binary numbers.

2.1.3 Examples for Decimal Sequences:

1) For p=1117

The binary sequence equivalent to the above decimal sequence is:

The period of binary sequence is 1116

The auto-correlation values of the above binary sequence are in the below graph:



Figure 2.2. Autocorrelation for binary sequence generated using p=1117; period = 1116.

2) For p = 1541

The binary sequence equivalent to the above decimal sequence is:

The length of decimal sequence is 1541

The period of the binary sequence is 1540

The auto-correlation values of the above binary sequence are in the below graph:



Figure 2.2. Autocorrelation for binary sequence generated using p=1541; period = 1540.

3) For p = 1861

The binary sequence equivalent to the above decimal sequence is:

The length of decimal sequence is 1861

The period of the binary sequence is 1860



The auto-correlation values of the above binary sequence are in the below graph:



2.1.4 Randomness measured by Autocorrelation Function:

For simplicity, we consider only the autocorrelation function as measure of randomness. Since the randomness measure of discrete-time white noise sequence is 1 whereas that of a constant sequence is 0, this measure conforms to our intuitive expectations. The value of randomness for a binary shift register maximum-length sequence is close to 1, in accord with our expectations. The function for a maximum-length d-sequence is has a negative peak of -1 for half the period because of the anti-symmetry of the sequence.

Randomness may be quantified by measuring how much the autocorrelation departs from the ideal of white noise. Kak defines this randomness measure R(x) [26] by the expression below:

$$R(x) = 1 - \frac{\sum_{k=1}^{n-1} |C(k)|}{n-1}$$

I have calculated the randomness measure for several d-sequences which have the results as follows:

R(1117) = 0.986390678R(1861) = 0.990382

R(2843) = 0.993393

This shows that d-sequences are quite random from the perspective of this measure.

2.2 Binary sequences from Windows PC

Different random number generators are used for PC applications. Here I have taken an online random number generator and generated random numbers to determine their autocorrelation function. I downloaded the random number generator from <u>www.cnet.com</u> to my PC where it asks for the type of random sequence to be generated, such as decimal, binary etc, and also the length of the sequence.

The binary random sequence generated for a length of 2000 is shown below:

The auto-correlation values of the above binary sequence are in the below graph:



Figure 2.5. Autocorrelation for binary sequence generated from windows PC.

The randomness measure for this binary sequence is:

$$R(x) = 0.981007$$

This value is lower than the values found for d-sequences. But just this fact should not lead to the conclusion that d-sequences are superior owing to their obvious structure in the sense that the second half of the sequence is a complement of the first half.

CHAPTER III

MESH ARRAY SCRAMBLING OF NUMBERS

This chapter presents the use of mesh array for matrix multiplication [27]-[28] for generating random sequences.

3.1 Standard and Mesh Arrays:

In contrast to the standard array that requires 3n-2 steps to complete its computation, the mesh array requires only 2n-1 steps[27].

When we consider the problem of matrix multiplication, the standard array to compute the product of two 3×3 matrices is shown in Figure 3.1. It can be easily seen that the number of steps to solve this problem is (3n-2). The numbers inside the circle are the indices of the product matrix.



Figure 3.1: Standard Array matrix multiplication of two 3×3 matrices

The mesh array [27] of Figure 3.2 is more efficient than the standard array of Figure 3.1. The time taken to execute matrix multiplication on it is (2n-1).

3.2 Matrix Multiplication on a Mesh Array:

Matrix multiplication[27]-[28] is basic to many computational problems. In signal processing, the signal is usually transformed by a matrix. For an image the signal itself is a matrix, and for a one-dimensional signal, a large data set can be represented as a matrix.

Figure 3.2 presents the mesh array for multiplying two 4×4 matrices which takes 7 steps, whereas the standard array requires the same number of steps to multiply two 3×3 matrices. The speedup of the mesh array is a consequence of the fact that no zeros are padded in its inputs.



Figure 3.2: Mesh Array matrix multiplication of two 4×4 matrices C = AB

In the mesh array for the matrix multiplication the top layer has the diagonal terms 11, 22, 33, etc as goes from left to right. These numbers are written in the array as below.

We can see that the fourth row is the mirror reversed image of the second row and the third row has symmetry within itself.

For the 5×5 matrix, the product components are as follows:

3.3 Scrambling Transformations:

We have seen that the product matrix values do not appear in the standard arrangement[28]. The new arrangement when a matrix is multiplied with the identity matrix may be called scrambling transformation S. Given a total of $n \times n = n^2$ items, the total number of permutations is n^2 !.



Figure 3.3: Mesh Array matrix multiplication of matrix A with Identity Matrix

Let the scrambling transformation is denoted by S, if the scrambling transformation is applied repeatedly, we obtain the original standard array in some number of steps. For the 4×4 matrix, the original array will be obtained in 7 steps[28].

11	12	13	14	S	11	22	33	44	S^2	11	31	41	21	S^3
21	22	23	24	\rightarrow	12	31	24	43	\rightarrow	22	32	43	13	\rightarrow
31	32	33	34		32	14	41	23		14	44	34	24	
41	42	43	44		34	42	13	21		23	42	33	12	
11	32	34	12	S^4	11	14	23	22	S^5	11	44	24	31	S^6
31	14	43	13	\rightarrow	12	31	24	42	\rightarrow	14	21	41	34	\rightarrow
44	21	23	43		21	12	24	13		12	22	43	33	
24	42	41	22		43	42	34	31		13	42	23	32	
11	21	43	32	S^7	11	12	13	14						
44	12	34	23	\rightarrow	21	22	23	24						
22	31	13	41		31	32	33	34						
33	42	24	14		41	42	43	44						

3.3.1 Generating Cycles:

As shown in [28], the items of both standard array and mesh array for the 4×4 case will be written in an array as follows:

11 12 13 14 21 22 23 24 31 32 33 34 41 42 43 44 (11 22 33 44 12 31 24 43 32 14 41 23 34 42 13 21 By using the above arrangement, we can write the standard and mesh arrays into cycles. The cycles generated from the above arrangement are as follows:

= (11) (42) (12 22 31 32 14 44 21) (13 33 41 34 23 24 43)

By writing the standard array and mesh array into cycles, we get the period of the scrambling transformations. The period is nothing but the maximum of lengths of the cycles since the lengths of the cycles are $\{1,1,7,7\}$, the period of the scrambling transformation = 7.

3.3.2 Prime Periods:

Some periods of the cycles associated with matrices of order $n \times n$ are prime. Over the range of n from 2 to 1000, the matrices associated with prime periods have the following distribution[29]:

- 101 200 ---- 15
- 201 300 ---- 10
- 301 400 ---- 11
- 401 500 ---- 5
- 501 600 ---- 3
- 601 700 ---- 8
- 701 800 ---- 5
- 801 900 ---- 4

• 901 – 1000---- 12

3.4 Generating Binary Sequence:

We can create a binary sequence of the periods in terms of 1s and 0s where the even period is represented as 1 and odd period is represented as 0[29]. The binary sequence for the periods of orders 2 to 1000 is as follows:

The autocorrelation function for k ranging from 0 to 1000 is shown in Figure 3.4.



Figure 3.4: Autocorrelation Function of periods of mesh array

The randomness measure for random sequence generated from the Mesh Array is:

$$R(x) = 0.972194$$

This is quite close to but not as high as the values obtained for d-sequences.

CHAPTER IV

CRYPTOGRAPHIC HARDENING OF PSEUDORANDOM SEQUENCES

In this chapter, we investigate results of a method of cryptographic strengthening of RNGs. Basically the idea is to apply a many-to-one mapping to the binary output of the RNG, increasing the complexity of the reverse process. We wish to consider the use of a 3-to-1 and higher mappings where each group of 0s and 1s is replaced by whatever is the majority to see if it improves the autocorrelation function of the resultant sequence. This will be tried both for the Windows based RNGs as well as d-sequences

4.1 The PR(n) Sequence:

The PR(n) sequences[32] emerges by mapping each group of adjacent n bits (n odd) of the PR sequence to 0 or 1 depending on whether it has a majority of 0s or 1s. We have done experiments on many d-sequences and we find that PR(3) provides significant improvement and that there is no significant advantage in taking larger values of n.

Let us take some examples for d-sequences, then the PR(n) sequences will be as follows:

P=1571:

Original Sequence or PR(1):



Figure 4.1: Autocorrelation function for PR(1) for 1/1571

3-numbers or PR(3):



Figure 4.2: Autocorrelation function for PR(3) for 1/1571

The autocorrelation function in Figure 4.2 is better than that in Figure \$.1 because the negative peak for half the sequence has been reduced.

5 numbers or PR(5):



Figure 4.3: Autocorrelation function for PR(5) for 1/1571

The autocorrelation function in Figure 4.3 is unchanged for Figure 4.1 as 5 divides 1570.

7 numbers or PR(7):



Figure 4.4: Autocorrelation function for PR(7) for 1/1571

9 numbers or PR(9):



Figure 4.5: Autocorrelation function for PR(9) for 1/1571

11 numbers or PR(11):



Figure 4.6: Autocorrelation function for PR(11) for 1/1571

From the above graphs, we can say that the negative peak for half the period gets smaller and smaller as we increase n in PR(n) and the improvement in randomness for PR(11) is quite impressive.

The tables below provide the list of the largest values of the autocorrelation function for the given sequences. The off-1 or -1 values are 0.33 and -0.33 for PR(1). We see that these values have reduced to 0.11 and -0.13 for the d-sequence corresponding to 1907[32]. There is corresponding improvement (not necessarily of the same extent) for the other examples given below.

1541:

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-1.0	-0.26	-0.28	-0.19	-0.22	-0.31
0.33	0.94	0.74	0.65	0.86	-0.94
-0.33	-0.24	-0.26	-0.15	-0.17	-0.27
0.19	0.71	0.47	0.51	0.74	-0.88
-0.19	-0.21	-0.21	-0.14	-0.13	-0.24
0.14	0.57	0.31	0.42	0.49	-0.77
-0.14	-0.19	-0.19	-0.12	-0.08	-0.21

Table 4.1: Reduction in the largest value Autocorrelation function values for d-sequence 1541

1907:

Table 4.2: Reduction in the largest value Autocorrelation function values for d-sequence 1907

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-1.0	-0.50	-0.37	-0.46	-0.81	-0.38
0.33	0.11	0.11	0.18	0.19	0.26
-0.33	-0.13	-0.12	-0.13	-0.21	-0.17
0.20	0.08	0.10	0.12	0.18	0.18
-0.20	-0.10	-0.11	-0.12	-0.20	-0.16
0.14	0.07	0.09	0.10	0.17	0.17
-0.14	-0.07	-0.10	-0.10	-0.18	-0.13

2243:

Table 4.3: Reduction in the largest value Autocorrelation function values for d-sequence 2243

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-1.0	-0.49	-0.38	-0.42	-0.39	-0.80
0.33	0.19	0.12	0.11	0.12	0.2
-0.33	-0.12	-0.09	-0.19	-0.21	-0.2
0.19	0.09	0.11	0.10	0.11	0.19
-0.19	-0.08	-0.07	-0.11	-0.20	-0.19
0.14	0.08	0.10	0.09	0.10	0.14

-0.14	-0.07	-0.06	-0.09	-0.19	-0.14

2333:

Table 4.4: Reduction in the largest value Autocorrelation function values for d-sequence 2333

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-1.0	-0.52	-0.40	-0.39	-0.35	-1.0
0.33	0.09	1.13	0.12	0.15	0.21
-0.33	-0.10	-0.11	-0.17	-0.21	-0.21
0.19	0.06	0.08	0.11	0.14	0.19
-0.19	-0.09	-0.09	-0.14	-0.18	-0.19
0.14	0.05	0.07	0.10	0.12	0.18
-0.14	-0.08	-0.08	-0.13	-0.15	-0.18

2843:

Table 4.5: Reduction in the largest value Autocorrelation function values for d-sequence 2843

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-1.0	-0.44	-0.4	-1.0	-0.74	-0.4
0.33	0.17	0.15	0.17	0.14	0.10
-0.33	-0.16	-0.10	-0.17	-0.12	-0.19
0.19	0.07	0.10	0.16	0.11	0.09
-0.19	-0.10	-0.08	-0.16	-0.10	-0.18
0.14	0.06	0.09	0.15	0.10	0.08
-0.14	-0.07	-0.07	-0.15	-0.09	-0.13

It should also be noted that the performance of PR(n) for a larger value of n does not always imply improved results as far as the autocorrelation function is concerned.

4.2 PR(n) sequences from Windows PC:

For binary sequences generated by random number generators in windows PC the performance of many-to-one mapping on the quality of the autocorrelation function is given in the table below:

The results for the windows PC RNG are shown in the table below:

PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-0.07	-0.12	-0.15	-0.19	-0.20	-0.16
0.06	0.10	0.14	0.18	0.16	0.19
-0.06	-0.10	-0.14	-0.15	-0.14	-0.15
0.05	0.09	0.12	0.16	0.14	0.18
-0.05	-0.09	-0.13	-0.14	-0.13	-0.12
0.04	0.08	0.11	0.15	0.13	0.13
-0.04	-0.08	-0.10	-0.13	-0.12	-0.11

Table 4.6: The largest value autocorrelation values for Windows RNG

We see that the use of applying the many-to-one mapping does not improve the autocorrelation

function of this RNG.

4.3 Mesh PR(n) Sequence:

The results of autocorrelation function for PR(n) sequence are given in the table below:

Table 4.7: The largest value autocorrelation values for the mesh array sequence

-					
PR(1)	PR(3)	PR(5)	PR(7)	PR(9)	PR(11)
1.0	1.0	1.0	1.0	1.0	1.0
-0.08	-0.14	-0.22	-0.18	-0.19	-0.23
0.08	0.12	0.22	0.19	0.19	0.17
-0.07	-0.13	-0.16	-0.16	-0.17	-0.15
0.07	0.11	0.18	0.18	0.18	0.15
-0.06	-0.11	-0.15	-0.15	-0.16	-0.13
0.06	0.10	0.14	0.15	0.15	0.13
-0.05	-0.10	-0.12	-0.13	-0.14	-0.10

The performance of the mesh array sequence to the many-to-one mapping is similar to that for the windows RNG.

4.4 Nested PR(n) Sequences:

Nested PR(n) sequences are nothing but taking the PR(n) sequences for the PR(n) sequences. Below table shows the nested PR(n) sequences for Windows PC. It is significant that the performance of nested PR(n) sequences for the windows PRNG is not very good as given by the results in the table below:

Table 4.8: Nested values for windows RNG

PR(1)	PR(3)	PR3(3)	PR3(PR3(3))
1.0	1.0	1.0	1.0
-0.07	-0.12	-0.12	-0.21
0.06	0.10	0.15	0.18
-0.06	-0.10	-0.10	-0.18
0.05	0.09	0.14	0.16
-0.05	-0.09	-0.09	-0.13
0.04	0.08	0.13	0.13
-0.04	-0.08	-0.08	-0.10

The randomness measure for the random sequences and PR(n) sequences are calculated as follows:

	P-1117	P-1861	P-2843	Win PC	Mesh Array
	1 – 1117	1 -1001	1-2045	vill i C	Wiesh miray
PR(1)	0.986390678	0.990382	0.993393	0.981007	0.972194
PR(3)	0.951072	0.964047	0.977966	0.966357	0.950941
PR(5)	0.943512	0.945826	0.968162	0.954581	0.940452
PR (7)	0.932415	0.943862	0.949445	0.947845	0.923323
PR(9)	0.896452	0.93822	0.949137	0.935778	0.896104
PR (11)	0.892918	0.935363	0.943303	0.930733	0.895849

Table 4.9: PR(n) values for all the sequences

From the above examples, we can see that the majority of d-sequences have the highest value of randomness measure for the PR(3) sequence.

For Windows PC, the randomness measure value is high for the PR(11) sequence and is very low for PR(9) sequence. For Mesh Array, the randomness measure value is high for the PR(7)sequence and is very low for PR(11) sequence. As mentioned before, for Windows PC and Mesh Array, the use of applying the many-to-one mapping does not improve the randomness measure value.

CHAPTER V

CONCLUSION

From the analysis of the above random sequences, we conclude that d-sequences have an excellent randomness measure. However, they are not cryptographically strong when compared to the random sequences generated from Windows PC and the mesh array random sequences because of the linear structure behind their generation. We have used many-to-one mappings to improve the cryptographic strength of d-sequences.

For the autocorrelation function of d-sequences, we can see that in many cases the negative peak for half period gets progressively smaller as we increase n in PR(n). The best results are obtained when n=3. However, the use of applying the many-to-one mapping does not improve the autocorrelation function for random sequences from Windows PC and Mesh random sequences.

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Cryptographically strong random sequences are essential in cryptography, digital signatures, challenge-response systems, and in Monte Carlo simulation. This thesis examines techniques for cryptographic hardening of random sequences that are not cryptographically strong. Specific random sequences that are considered include d-sequences, that is sequences that are reciprocals of primes, and a new sequence obtained by the use of a specific two-dimensional mesh array.

Findings and Conclusions:

It is shown that the use of many-to-one mapping on blocks of the raw sequence improves the quality of autocorrelation function. Various types of many-to-one mappings are used and their effect on the autocorrelation function is compared. Sequences are also compared using another measure of randomness.