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The need for random and pseudorandom numbers arises in many cryptographic applications. For example, common cryptosystems employ keys that must be generated in a random fashion. Many cryptographic protocols also require random or pseudorandom inputs at various points, e.g., for auxiliary quantities used in generating digital signatures, or for generating challenges in authentication protocols.

This document discusses the randomness testing of random number and pseudorandom number generators that may be used for many purposes including cryptographic, modeling and simulation applications. The focus of this document is on those applications where randomness is required for cryptographic purposes. A set of statistical tests for randomness is described in this document. The National Institute of Standards and Technology (NIST) believes that these procedures are useful in detecting deviations of a *binary sequence* from randomness. However, a tester should not assume that apparent deviations from randomness may be due to either a poorly designed generator or to anomalies that appear in the binary sequence that is tested (i.e., a certain number of failures is expected in random sequences produced by a particular generator). It is up to the tester to determine the correct interpretation of the test results. Refer to Section 4 for a discussion of testing strategy and the interpretation of test results.

1.1.2 Unpredictability

Random and pseudorandom numbers generated for cryptographic applications should be unpredictable. In the case of PRNGs, if the seed is unknown, the next output number in the sequence should be unpredictable in spite of any knowledge of previous random numbers in the sequence. This property is known as forward unpredictability. It should also not be feasible to determine the seed from knowledge of any generated values (i.e., backward unpredictability is also required). No correlation between a seed and any value generated from the seed should be evident; each element of the sequence should appear to be the outcome of an independent random event whose probability is $1/2$.

To ensure forward unpredictability, care must be exercised in obtaining seeds. The values produced by a PRNG are completely predictable if the seed and generation algorithm are known. Since in many cases the generation algorithm is publicly available, the seed must be kept secret and should not be derivable from the pseudorandom sequence that it produces. In addition, the seed itself must be unpredictable.

1.1.3 Random Number Generators (RNGs)

The first type of sequence generator is a random number generator (RNG). An RNG uses a non-deterministic source (i.e., the entropy source), along with some processing function (i.e., the entropy distillation process) to produce randomness. The use of a distillation process is needed to overcome any weakness in the entropy source that results in the production of non-random numbers (e.g., the occurrence of long strings of zeros or ones). The entropy source typically consists of some physical quantity, such as the noise in an electrical circuit, the timing of user processes (e.g., key strokes or mouse movements), or the quantum effects in a semiconductor. Various combinations of these inputs may be used.

The outputs of an RNG may be used directly as a random number or may be fed into a pseudorandom number generator (PRNG). To be used directly (i.e., without further processing), the output of any RNG needs to satisfy strict randomness criteria as measured by statistical tests

Pseudorandom Number Generators (PRNGs)

The second generator type is a pseudorandom number generator (PRNG). A PRNG uses one or more inputs and generates multiple “pseudorandom” numbers. Inputs to PRNGs are called **seeds**. In contexts in which unpredictability is needed, the seed itself must be random and unpredictable. Hence, by default, a PRNG should obtain its seeds from the outputs of an RNG; i.e., a PRNG requires a RNG as a companion.

The outputs of a PRNG are typically deterministic functions of the seed; i.e., all true randomness is confined to seed generation. The deterministic nature of the process leads to the term “pseudorandom.” Since each element of a pseudorandom sequence is reproducible from its seed, only the seed needs to be saved if reproduction or validation of the pseudorandom sequence is required.

Ironically, pseudorandom numbers often appear to be more random than random numbers obtained from physical sources. If a pseudorandom sequence is properly constructed, each value in the sequence is produced from the previous value via transformations which appear to introduce additional randomness. A series of such transformations can eliminate statistical autocorrelations between input and output. Thus, the outputs of a PRNG may have better statistical properties and be produced faster than an RNG.

Various statistical tests can be applied to a sequence to attempt to compare and evaluate the sequence to a truly random sequence. Randomness is a probabilistic property; that is, the properties of a random sequence can be characterized and described in terms of probability. The likely outcome of statistical tests, when applied to a truly random sequence, is known a priori and can be described in probabilistic terms. There are an infinite number of possible statistical tests, each assessing the presence or absence of a “pattern” which, if detected, would indicate

accept H_0

H_0 will be accepted if the data is really random, and to reject H_0 will be accepted if the data is not random.

called the *level of significance* of the test. This is denoted by α (alpha), which is usually set at 0.05 (5%). This is the probability of rejecting H_0 when it is really random, and to reject H_0 will be accepted if the data is not random.

| TRUE SITUATION | |
|-------------------------------------|----------|
| Data is random (H_0 is true) | No error |
| Data is not random (H_a is true) | Error |

If the data is, in the

critical value is determined by the level of significance, α , and the sample size, n .

data (the sequence being tested). This test statistic value exceeds the critical value, the null hypothesis is rejected.

Otherwise, the null hypothesis (the randomness hypothesis) is accepted.

(reject H_0)

a sequence that appears to have a random property. Unlike
 an infinite number of other sequences, the Type I error is not difficult to calculate. It is caused by the many possible types
 of sequences, i.e., to minimize the probability of
 when the generator was actually bad
 the size n of the tested sequence in s
 probability of a Type I error

true) = $P(\text{reject } H_0 | H_0 \text{ is true})$, and the Type I
 $P(\text{accept } H_0 | H_0 \text{ is false})$. The test statistic is

1.1.6 Considerations for Randomness, Unpredictability and Testing

The following assumptions are made with respect to random binary sequences to be tested:

1. Uniformity: At any point in the generation of a sequence of random or pseudorandom bits, the occurrence of a zero or one is equally likely, i.e., the probability of each is exactly $1/2$. The expected number of zeros (or ones) is $n/2$, where n = the sequence

Since various tests can be applied to subsequences, the any such extracted subsequence should pass any test for

Definition

approximately normal with Uean \bar{x} and Variance $\frac{s^2}{n}$. The size increases.

| | |
|--|--|
| Run | An uninterrupted sequence of like bits (i.e., either all zeroes or all ones). |
| Seed | The input to a pseudorandom number generator. Different seeds generate different pseudorandom sequences. |
| SHA-1 | The Secure Hash Algorithm defined in Federal Information Processing Standard 180-1. |
| Standard Normal Cumulative Distribution Function | See the definition in Section 5.5.3. This is the normal function for mean = 0 and variance = 1. |

1.3 Mathematical Symbols

In general, the following notation is used throughout this document. However, the tests in this

S

The standard deviation of a random variable = $\sqrt{f(-)}$

The NIST Test Suite is a statistical package consisting of 16 tests that were developed to test the randomness of (arbitrarily long) binary sequences produced by either hardware or software based cryptographic random or pseudorandom number generators. These tests focus on a variety of different types of non-randomness that could exist in a sequence. Some tests are decomposable into a variety of subtests. The 16 tests are:

1. The Frequency (Monobit) Test,
2. Frequency Test within a Block,
3. The Runs Test,
4. Test for the Longest-Run-of-Ones in a Block,
5. The Binary Matrix Rank Test,
6. The Discrete Fourier Transform (Spectral) Test,
7. The Non-overlapping Template Matching Test,
8. The Overlapping Template Matching Test,
9. Maurer's "Universal Statistical" Test,
10. The Lempel-Ziv Compression Test,
11. The Linear Complexity Test,
12. The Serial Test,
13. The Approximate Entropy Test,
14. The Cumulative Sums (CUSUM) Test,
15. The Random Excursions Test, and
16. The Random Excursions Variant Test.

This section provides a discussion of the 16 tests and their subtests. The each test is discussed in detail in Section 2.11.

Section 4 provides a discussion of testing strategy and the interpretation of test results. The order of the application of the tests in the test suite is arbitrary. However, it is recommended that the Frequency test be run first, since this supplies the most basic evidence for the existence of non-randomness in a sequence, specifically, non-uniformity. If this test fails, the likelihood of other tests failing is high. (Note: The most time-consuming statistical test is the Linear Complexity test; see Sections 2.11 and 3.11).

Section 5 provides a user's guide for setting up and running the tests, and a discussion on program layout. The statistical package includes source code and sample data sets. The test code was developed in ANSI C. Some inputs are assumed to be global values rather than calling parameters.

A number of tests in the suite have the

14
distribution (i.e., the bell-shaped curve) is used to compare the value of the test statistic obtained from the RNN with the expected normal distribution of the test statistic under the assumption of randomness. The

$z \neq \sqrt{2_{obs}}$; see Section 3.1) is distributed as nW_{rml} , then z is distributed as half nW_{rml} .) If the sequence is random then the plus and minus ones will tend to cancel one another out so that the test statistic will be about 0. If there are too many ones or too many zeroes then the test statistic will tend to be larger than zero.

2.1.4 Test Description

of -1 and $+1$ and the Q -value of the input sequence X are converted to values X_1, X_2, \dots, X_n , where $X_i = 2e^{-Q_i}$ for $i = 1, 2, \dots, n$.

2.1.3 Test Statistic and Reference Distribution

The observed Q -value of the input sequence X is Q_{obs} . The Q -value of the sum of the X_i is Q_{sum} . The test statistic is $T = (Q_{obs} - Q_{sum}) / \sqrt{n}$, where n is the length of the sequence.

S_V or s_{Wbs} being

large in large positive values of S and large negative values of S

2.1.7 Input Size Recommendations

It is recommended that each the V or W be tested consist of a Uniform U of 100 bits (i.e., n^3

degenerates to W test

Additional input used by the function, but supplied by the testing code:

- ε The sequence of bits as generated by the RNG or PRNG being tested; this exists as a global structure at the time of the function call;

The focus of this test is the total number of runs in the sequence, where a run is an uninterrupted sequence of identical bits. A run of length r consists of exactly r identical bits and is bounded before and after with a bit of opposite value. The purpose of the runs test is to determine whether the number of runs of ones and zeros of various lengths is as expected for a random

Since the test is not applicable, the runs test is applicable.

Compute the test statistic

2.3.7 Input Size Recommendations

Q.E.,

For the example in this section, since

212.36 TD /F6 12 Tf 0.0144 Tc (2.3.8) Tj 45 0 TD 0.0171 Tc
000010001 Tc 0110001801100011001100018100010111000

128 8
6272 128

| | |
|---------|----|
| | |
| | |
| 750,000 | 40 |

N The number of blocks; selected in accordance with the value of M .

Test Statistic and Reference Distribution

A measure of how well the observed longest run length L_P within M -bit blocks matches the expected longest run length L_P within M -bit blocks. The reference distribution for the test statistic Q_c is a distribution.

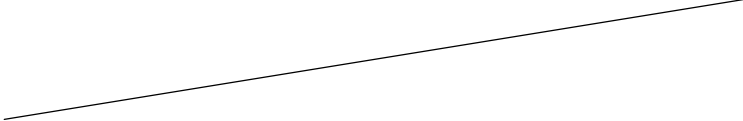
2.4.4

| |
|--|
| |
| |

| | | |
|-----------------|---|----|
| 128 | | 49 |
| 10 ⁴ | 6 | |

2
 For the example Wf 2.4.8,
 $0.00040 \quad T D \quad 0 \quad T c \quad (187)$

| | | | |
|--|--|--|--------|
| | | | 882605 |
|--|--|--|--------|



2.5.3 Test Statistic and Reference Distribution

$\chi^2(obs)$: A measure of how well the observed number of runs of various orders match the expected number of runs under an assumption of randomness.

The reference distribution for the test statistic is a χ^2 distribution.

2.5.4 Test Description

(1) Sequentially divide the sequence into M Q -bit disjoint blocks; there will exist

$$\left\lfloor \frac{n}{3 \cdot 3} \right\rfloor = 2 \text{ matrices of cardinality } M \cdot Q \text{ (3)}$$

bits (0 and 1) will be dis

$$\frac{\quad)}{.2888} \quad \frac{(\quad 10.5776 \quad 2)}{\quad} \quad \frac{(\quad 1 \quad 1 \quad 0.1336 \quad 2)}{0.}$$

(processing) \mathbf{c}^2

(output) $P\text{-value} = 0.532069$

found pattern, and the search resumes. —

2.7.2 FunctioV CalT

NonOverlappingTemplateMatching(U, n)

U The length in bQts of each template. The template is the tar.6.t string.

A d value that is too low would indicate that there were too few peaks ($< 95\%$) below T , and too many peaks (more than 5%) above T .

n The length of the entire bit string under test.

Additional input used by the function, but supplied by the testing code:

ϵ The 6 quence of bits as generated by the RNG or PRNG being tested; this exists as a global structure at the time of the function call: $\epsilon = \epsilon_1, \epsilon_2, \dots, \epsilon_n$.

B The bit string of the template B (of length m)

h is defined in a template library of non-periodic patterns contained within test code.

generated bit string of length 1072
Statistic and Reference Distribution

asure of how well the observed number of template “hits” matches the expected number of template “hits” (under an assumption of randomness).

ion for the test statistic is the χ^2 distribution.

on

ence into N independent blocks of length M .

and $M = 10$, then the

—

is a match

window slides over m

then the next window will contain bits 6 to 8.

For the above example, if $U = 3$ and the template $B = 031712$ then the examination proceeds as follows:

B01 1 0 W 111

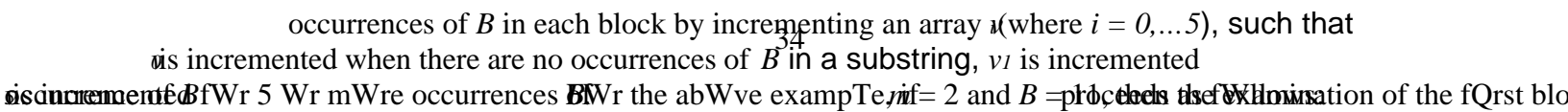


8-10

| | | | | | |
|-----------|-----------|--------------|----------------|--------------|--|
| | 2-4 | 010 | 110 | | |
| | 3-5 | 100 | 100 | | |
| | 001 (hit) | Increment to | 001 (hit) | Increment to | |
| | 5-7 | Not examined | | Not examined | |
| | 6-8 | Not examined | | Not examined | |
| | 7-9 | 001 | Increment to 2 | 011 | |
| 010 (hit) | 2 | 110 | | | |

Thus, $W_1 = 2$, and

If the *P-value* is very small (< 0.01), then the sequence has irregular occurrences of the possible template patterns.



$$\text{Compute } P\text{-value} = \text{igamc} \left(\frac{c^2(\text{obs})}{5 \cdot 0.324652}, \frac{(51 - 0.106645)}{5 \cdot 0.077147}, \frac{(1 \pm 5 \cdot 0.142670)}{5 \cdot 0.166269} \right)$$

$$\left(\frac{5}{2}, \frac{c^2(\text{obs})}{2} \right)$$

For the example in this section, $P\text{-value} = \text{igamc}$

$$\chi^2_{2, 0.975} = 3.167729 \Rightarrow P\text{-value} = 0.274932.$$

2.8.5 Decision Rule (at the 1 % Level)

If the computed $P\text{-value}$ is < 0.01 , then conclude that the sequence is non-ravdom. Otherwise, conclude that the sequence is ravdom.

2.8.6 Conclusion and Interpretation of Test Results

Since the $P\text{-value}$ obtained in step 4 of Section 2.8.4 is ≥ 0.01 ($P\text{-value} = 0.274932$), the conclusion is that the sequence is ravdom.

2.8.7 Input Size Reductions The input size of a sequence of length N is $2N$ bits. The input size of a sequence of length N is $2N$ bits.

The values of K and M have been chosen such that each sequence to be tested contains a minimum of 10 bits ($Q_{\min} = 10$). Various values of U and N are considered.

- N should be chosen such that $N \geq 2(M+U)/2$
- U should be chosen such that $U \geq 2(M+U)/2$

268.8 Example

(input) \mathbf{e} = the binary expansion of e up to 1,000,000 bits



f : The distance between matching L -bQt templates, i.e., the sum of the number of digQts in the distance between L -bQt templates.

The reference distribution for the test statistic is the Half-normal distribution

| Initialization | 0 | 00 (saved in T_0) | 01 (saved in T_1) | 10 (saved in T_2) | 11 (saved in T_3) |
|----------------|---|-------------------------|-------------------------|-------------------------|-------------------------|
| | | 24 | 0 | | |

(3) Examine each of the 4 blocks in the test segment and determine the number of blocks between the last occurrence of the same block and the current block (i.e., the distance between occurrences of the same block to an accumulating sum). Add the calculated distance to the sum of all the T_i (i.e., if T_i is the current block (i.e., the block being examined), and $sum = 5.169925002 + 0 = 5.169925002$. The 01 row of the table (i.e., T_1), and $sum = 5.169925002$ table (i.e., T_1),

| Iteration BTock | | | | |
|--------------------|----|----|----|----|
| | 00 | 01 | 10 | 11 |
| 4 | 0 | 2 | 4 | 0 |
| 5 | 0 | 5 | 4 | 0 |
| 6 | 0 | 5 | 4 | 6 |
| 7 | 0 | 7 | 4 | 6 |
| 8 | 0 | 8 | 4 | 6 |
| 9 | 0 | 9 | | |
| 10 | 0 | 9 | | |

For the example in the section, the following table Qs created 38 blocks.

Compute $P\text{-}value = \text{erfc}$

2.9.6 Conclusion and Interpretation of Test Results

Since the *P-value* obtained in step 5 of Section 2.9.4 is ≥ 0.01 (P-value = 0.125), the conclusion is that the sequence is random.

(processing) $f_n = 6.194107$, $expectedValue = 6.196251$, $\mathbf{s} = 3$

(output) $P\text{-value} = 0.427733$

| | | | |
|----------|---|-----|-----------|
| | | | |
| 1 | 0 | Yes | 0 (Bit 1) |
| 2 | 1 | Yes | |

10.7 Input Size Recommendations

It is recommended that each sequence to be tested consist of a U
 $n \in [10^6]$

11.3 Test Statistic and Reference Distribution

$\chi^2(obs)$: A measure of how well the observed number of observed
LESRs matches the expected number of occurrences

$$, \quad {}^w p_0 = p_1 01047, \quad p_2 \overset{\ddot{0}}{\underset{\cdot}{\div}} \mathfrak{c}$$

1.7 Input Size recommendations

Choose $n \leq 10^6$. The value of M must be in the range $500 \leq M \leq 10^6$. The result will be valid (see Section 3.11 for a discussion).

(4) Compute: $y - y - y^2$ ₁

#00s = 250116; #01s = #10s = 249855; #11s = 250174

(processing) $\chi^2_{\text{y}} = 2.0438400$ $\tilde{\chi}^2_{\text{y}} = 2.33676400$ $P = 0.541964$; P -value

as random

(6) Compute the test statistic: $c^2 = 2n[\log 2 - ApEn(m)]$, where

(Conclusion) Since $P\text{-value} \geq 0.01$, accept the sequence as random.

2.14 Cumulative Sums (Cusum) Test

Mode = 1 (backward)

For the example in this section, $P\text{-value}_{54} = 0.4116588$.

2.14.5 Decision Rule (at the 1 % Level)

The focus of the test is the number of cycles having exactly K visits in a cumulative sum random walk. The cumulative sum random walk is derived from partial sums after the $(0,1)$ sequence is transferred to the appropriate $(-1, +1)$ sequence. A cycle of a random walk consists of a sequence of steps of unit length taken at random that begin at and return to the origin. The

$$S_k = X_1 + X_2 + \dots + X_k \qquad 56$$

.

$$S_n = X_{\emptyset, 0.036} \cdot T_c \cdot 0.036 \cdot T_w \cdot (+X) \cdot T_i \cdot \mathfrak{A} \cdot b^{36} \cdot T^* \cdot TD / F4 \cdot 8.04 \cdot T_f \cdot 0.06 \cdot T_c \cdot 0 \cdot T_w \cdot (2) \cdot T_i \cdot 4.08 \cdot 0.0356 \cdot TD / F4 \cdot 4 \cdot 1(f \cdot -0.036 \cdot T_c \cdot 0.036 \cdot T_w \cdot (+X) \cdot T$$

| | | | | |
|-----------|----------------|-----------------|---|---|
| | Cycle 1 | Cycle 21 | 0 | 0 |
| State x | (0, -1, 0) | | | |

| | | | |
|----------|---|---|---|
| | | | |
| 1 | 0 | 1 | 3 |
| 2 | 0 | 0 | 3 |
| 3 | 0 | 0 | |
| 4 | 0 | 0 | 0 |

V (the -1 state occurs exactly 0
 $V_1(-1) = 1$ (the -1 state occurs only once i
 $V_2(-1) = V_3(-1) = V_4(-1) \neq 0$ (the -1 state

55) For each cycle and for each non-zero state value x having
 4, compute the frequency of each x within each cycle

The focus of this test is the total number of times that a particular state is visited (i.e., occurs) in a cumulative sum random walk. The purpose of this test is to detect deviations from the expected number of visits to various states in the random walk. This test is actually a series of eighteen tests (and conclusions), one test and conclusion for each of the states: -9, -8, ..., -1 and

$$\left(\frac{|4-3|}{\sqrt{2 \cdot 3(4-2)}} \right)_{+0} = 0.683091.$$

See Section 5.5.3.3 for the definition of *erfc*.

For the example in this section, when $n=1$, *erfc* value =

$$\left(\frac{|4-3|}{\sqrt{2 \cdot 3(4-2)}} \right)_{+0} = 0.683091.$$

$$S_k = X_1 + X_2 + X_3 + \dots + X_k$$

3.1 Frequency (Monobit) Test

The most basic test is that of the null hypothesis: in a sequence of independent identically distributed Bernoulli random variables (X 's or ϵ 's, where $X = 2\epsilon - 1$, and so S

$= N$, i.e., tPe computed values of tPe longest run o(ne3(o)-2ones)-339(witPin)-324(eac)27(h)-
 $-r$ zeroes in tPe m -bit Tc2(lo)-27(c)27(k)0(,)-295(t)-2(Pen)-290(tPe)-299(c)2(onditional)-278(probabilit)23(y)]TJfl -14

$$\chi^U_j$$

—(3)

TPe tPeoretical probabilities

from (3), $0 \leq i \leq K$ of these classes s determined

Theoretical frequencies; K s coVjWined by tPe 2

$$\chi^K_i = \frac{\chi^K_i}{i^2}$$

which, under the randomness hypothesis, has an approximate distribution

$$K = 6; M = 10000$$

| | | | | |
|---------------|---------------|---------------|-------------|-------------|
| | $^+ 10g$ | $f^+ = 11g$ | $f^+ = 12g$ | $f^+ = 13g$ |
| probabilities | $_0 = 0.0882$ | $_1 = 0.2092$ | $_2$ | $= 0.1933$ |
| | $f^+ = 14$ | $^+ = 15g$ | $f^+ = 16$ | |

[1] battery of tests. It is based on the result of Kovalenko (1972) and also

Interpretation of this test: large values of $\chi^2(obs)$ indicate that the deviation of the rank distribution from that corresponding to a random sequence is significant. For example, pseudo random matrices produced by a shift-register generator for U ed by less than M successive vectors systematically have rank R M , while for truly random data, the proportion of such occurrences should be about 0.9.

References for Test

- [1] George Marsaglia, DIEHARD: a battery of tests of randomness.
- [2] I. N. Kovalenko (1972), "Distribution of the linear rank of a matrix," Theory of Probability and its Applications. 17, pp. 34-40.
- [3] G. Marsaglia and L. H. Tsay (1985), "Matrices and the random number sequences," Linear Algebra and its Applications. 147-156.

Uod

The test described here is based on the discrete Fourier transform. It is a member of a class of procedures known as spectral methods. The Fourier test detects periodic features in the bit series that would indicate a departure from the assumption of randomness.

Let x_k

$$x_k = \sum_{j=0}^{n-1} x_j \exp(2\pi i k j / n) \quad \text{where } \exp(2\pi i) = 1$$

be the modulus of the complex number f_j . Under the assumption of the randomness of the series x_i , a confidence interval can be placed on the values of f_j . More specifically, 95 percent of the values of f_j will lie within the interval $\pm \sqrt{2/n}$.

vaT_{ue} based on this threshold comes from the binomial distribution.
 be the number of peaks less than τ . Only the first 2 peaks are
 considered. Let 2 and 2) is the cumulative probability
 based on the series

that are sensitive to de-

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| OFFICE OF THE CHIEF OF SCHOOL OF DESIGN | |
| OFFICE OF THE CHIEF OF SCHOOL OF ARTS | |
| OFFICE OF THE CHIEF OF SCHOOL OF LETTERS | |
| OFFICE OF THE CHIEF OF SCHOOL OF SOCIAL SCIENCES | |
| OFFICE OF THE CHIEF OF SCHOOL OF HUMANITIES | |
| OFFICE OF THE CHIEF OF SCHOOL OF EDUCATION | |
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| OFFICE OF THE CHIEF OF SCHOOL OF PUBLIC RELATIONS | |
| OFFICE OF THE CHIEF OF SCHOOL OF POLITICAL SCIENCE | |
| OFFICE OF THE CHIEF OF SCHOOL OF ECONOMICS | |
| OFFICE OF THE CHIEF OF SCHOOL OF LAW | |
| OFFICE OF THE CHIEF OF SCHOOL OF MEDICAL STUDIES | |
| OFFICE OF THE CHIEF OF SCHOOL OF NURSING | |
| OFFICE OF THE CHIEF OF SCHOOL OF DENTISTRY | |
| OFFICE OF THE CHIEF OF SCHOOL OF VETERINARY MEDICINE | |
| OFFICE OF THE CHIEF OF SCHOOL OF AGRICULTURE | |
| OFFICE OF THE CHIEF OF SCHOOL OF FORESTRY | |
| OFFICE OF THE CHIEF OF SCHOOL OF MINING | |
| OFFICE OF THE CHIEF OF SCHOOL OF METALLURGY | |
| OFFICE OF THE CHIEF OF SCHOOL OF CHEMISTRY | |
| OFFICE OF THE CHIEF OF SCHOOL OF PHYSICS | |
| OFFICE OF THE CHIEF OF SCHOOL OF MATHEMATICS | |
| OFFICE OF THE CHIEF OF SCHOOL OF ENGINEERING | |
| OFFICE OF THE CHIEF OF SCHOOL OF ARCHITECTURE | |
| OFFICE OF THE CHIEF OF SCHOOL OF DESIGN | |
| OFFICE OF THE CHIEF OF SCHOOL OF ARTS | |
| OFFICE OF THE CHIEF OF SCHOOL OF LETTERS | |
| OFFICE OF THE CHIEF OF SCHOOL OF SOCIAL SCIENCES | |
| OFFICE OF THE CHIEF OF SCHOOL OF HUMANITIES | |
| OFFICE OF THE CHIEF OF SCHOOL OF EDUCATION | |
| OFFICE OF THE CHIEF OF SCHOOL OF BUSINESS | |
| OFFICE OF THE CHIEF OF SCHOOL OF JOURNALISM | |
| OFFICE OF THE CHIEF OF SCHOOL OF MASS COMMUNICATIONS | |
| OFFICE OF THE CHIEF OF SCHOOL OF PUBLIC RELATIONS | |

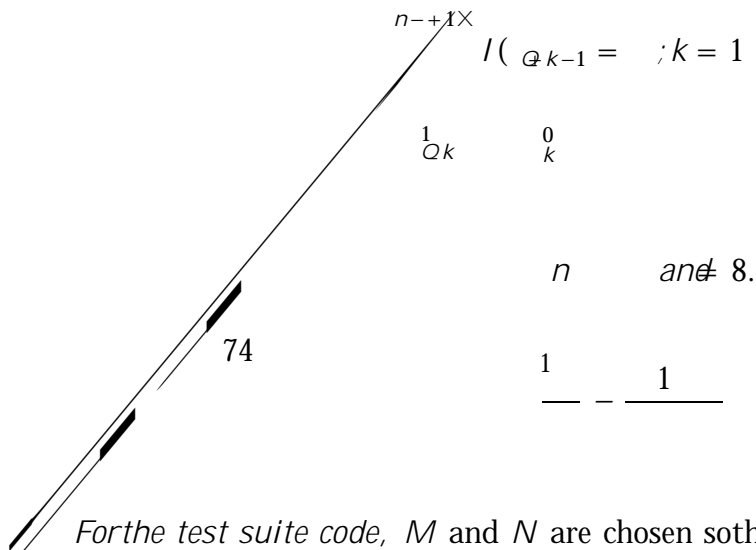
[illegible]

$(\frac{0}{1}; \dots; \frac{0}{m})$ be a given word (template or pattern, Q.e., a fixed sequence of zeros and ones) of length

$$0 \leq k \leq m$$

for a pattern C shorter than B with C^0 denoting a prefix of C). In this situation, occurrences of C^0 in the string are *non-overlapping*.

$= m; M$ be the number of occurrences of the given pattern in the string. Note that the statistic



$$; k = 1$$

Partition the original string into N blocks of length

-distribution with N degrees of freedom. Report the

P $val(l)11(u)34(e)]TJ/F10 1 Tf2.6+66 0 T00.004 Tc[(as)-321(1)]TJ/F+ 1 Tf1.915/F1 T00 Tc($

| | | | | | | | | | | | | | | $m\mathcal{B}$ | | | | | | |
|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|----------------|-----|-----|-----|-----|-----|-----|
| 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | | |
| | | | | | | | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | | |
| 0 | 0 | 0 | 1 | 1 | 1 | | | | | | | | | 0 | 0 | 0 | 0 | 0 | 1 | 0 |

The complement to the distribution function of random variable has the form

$$L(u) = P(U > u) = e^{-\sum_{k=u+1}^{\infty} \frac{1}{2^k}} \quad (1)$$

with

$$f(u) = \sum_{k=u}^{\infty} \frac{1}{2^k} = \frac{1}{2^{u-1}} \quad (2)$$

Choose K see or cite for

f

$U = 0$

$0, 1, \dots, K+1$

$K=5$

2;

$1, \dots, U_N$

0

$1 \quad K$

$$z = \frac{K}{Q - N} \quad (3)$$

P

[1] O. Chrysaphinou and S. Papastavridou, "A Limit Theorem on the Number of Overlapping Appearances of a Pattern in a Sequence of Independent Trials." *Probability Theory and Related Fields*, Vol. 79 (1988), pp. 129-143.

[2] N.J. Johnson, S. Kotz, and A. Kemp, *Discrete Distributions*. John Wiley, 2nd Ed. New York, 1996 (especially pp. 378-379).

$1, \dots, K$

$+$ \mathbb{N}

$$N_Q = \frac{Q}{Q-1}$$

3.9 Maurer's "Universal Statistical" Test

This test was introduced in 1992 by Ueli Maurer of Department of Computer Science at Princeton University. Maurer's statistic relates closely to the per-bit entropy of the stream, which he asserts is the correct

quality measure for a secret-key source in a cryptographic application. "As

such, the test is claimed to measure the actual cryptographic significance of a defect because it is related to the running time of [an] enemy's optimal key-search strategy," or the effective key size of a cipher system.

The test is not designed to aery specific pattern or type statistical defect. However, the test is designed to be able to detect any one of the very general class of statistical defects that can be modeled by an ergodic stationary source with finite memory." Because of this, Maurer claims that the test subsumes a number of the standard statistical tests.

The test is a compression-type test based on the idea of Ziv that a universal statistical test can be based on a universal source coding algorithm.

A generator should pass the test if and only if its output sequence cannot be compressed by more than a specified amount.

The test requires a long (on the order of 10^6)

$$+ 1000 \cdot 2^{-L} \text{ with } 6 \leq L \leq 16$$

sequence of bits which are divided into blocks of size L .

It should be specifically chosen to ensure that all possible L -bit

patterns occur with approximately equal frequency. The test is initialized with a seed value.

The algorithm achieves this efficiency by subscribing a dynamic look-up table using use of the integer representation of the binary bits constituting the template blocks. A standardized version of the statistic - the standardization being prescribed by the test - is compared to an acceptable range based on a standard Normal (Gaussian) density, using use of the test statistic's

$$= \frac{1}{L} \sum_{i=1}^L (1 - L_i)$$

is the of the random variable

1

A

and the $P - value$ is

$$\frac{f_n - E(L)}{\sqrt{\frac{1}{n} \text{var}(f_n)}}$$

References for Test

- [1] Ueli M. Maurer, "A Universal Statistical Test for Random Bit Generators," *Journal of Cryptology*. Vol. 5, No. 2, 1994, pp. 89-105.
- [2] J-S Coron and D. Naccache, "An Accurate Evaluation of Maurer's Universal Test," *Proceedings of SAC '98 (Lecture Notes in Computer Science)*. Berlin: Springer-Verlag, 1998.

The Lempel-Ziv test is thought to subsume the frequency, runs, order compression, and possibly spectral tests, but it may intersect the random binary matrix rank test. The test is similar to the entropy test and even more similar to Maurer's Universal Statistical test. However, the Lempel-Ziv test directly incorporates the compression heuristic that defines modern information theory.

There are several variations on the Lempel-Ziv algorithm (1977). The test used here assumes $2^{(l-1)/3}$ (Patil) $\log_2 10.5392$ 0 $\log_2 0$ $\log_2 0$ $\log_2 (f)$ $\log_2 1$ $\log_2 0$ proceeds as follows:

1. Parse the sequence into consecutive disjoint strings (words) so that the next word is the shortest string not yet seen.
2. Number the words consecutively in base i .
3. Assign each word a prefix and a suffix; the prefix is the number of the previous word that matches all but the last digit; the suffix is the last digit.

Note that what drives this compression is the fact that the compressed representation is usually longer than the original representation.

Following the work of Aldous and Shalunov (1988), $W(9) = EW(9) \log_2 10.5855$ 0 $\log_2 0.004$ $\log_2 (0)$ $\log_2 231$ the Lempel-Ziv compression. However, Aldous and Shalunov were unable to determine the value of $W(9)$.

TPat difficulty was nominally overcome by Kirschenhofer, Prodinger, and Szpankowski (1994) who prove tPat

$$^2[W(n)] \quad \frac{n[C + (\log_2 n)]}{\log_2^3 n}$$

-6.

The given sequence is parsed, and the number of words counted. It is not necessary to go through the complete Lempel-Ziv encoding, since the number of words, W

$\frac{3}{2}$

Dfl (ic)27(h)-408(i)-2(s)-423(t)-2(hen)-416(compared)-408(with)-408(a)-429(s)3(tandard)-408(nor

TPe P – *value* is computed as

1

$$- \frac{2dY}{\rho_2}$$

and 70.448718, respectively.

References for Test

- [1] D. Aldous and P. Shields (1988). "A Diffusion Limit for a Class of Randomly-Growing Binary Trees," *SIAM Journal on Computing*, 17, pp. 509-542.
- [2] L. Blum, M. Blum, and M. Shub (1994), "A Simple Unpredictable Pseudo-Random Number Generator," *SIAM Journal on Computing*, 23, pp. 364-383.
- [3] P. Kirschenhofer, "Search Trees Again Revisited: The Internal Path Length Perspective," *SIAM Journal on Computing*, 24, pp. 1041-1054.
- [5] J. Ziv and A. Lempel (1977), "A Universal Algorithm for Sequential Data Compression," *IEEE Transactions on Information Theory*, 24, pp. 678-691.

3.11 Linear Complexity Test

This test uses linear complexity to test for randomness. The concept of linear complexity is related to the concept of linear complexity in the theory of linear recurrences.

For a given sequence $S^n = (s_1, \dots, s_n)$, its linear complexity $L(S^n)$ is defined as the length of the shortest LFSR that generates S^n .

Let $\sigma_n = \text{Var}(L(S^n))$ be the variance of the linear complexity of the n -sequence S^n when S^n is truly random. The Crypt-X package [1] suggests that the ratio $\frac{\sigma_n}{n}$ tends to a standard normal variable, so that the corresponding p -values can be found from the error function. Indeed, Gustafson et al. [1] (p. 693) claim that $\frac{L(S^n)}{n}$ is approximately normally distributed with mean $\frac{1}{2}$ and a variance $\frac{81}{86}$ times that of the standard normal statistic $\frac{n}{2} - \frac{81}{86}$. This is completely false. Even the mean value does not behave asymptotically precisely as $\frac{1}{2}$, and in view of the boundedness of the variance, this difference becomes significant. More importantly, the tail probabilities of the limiting distribution are much larger than those of the standard normal distribution.

The asymptotic distribution of $(\frac{L(S^n)}{n} - \frac{1}{2})\sqrt{n}$ along the sequence of even and odd values of n is that of a discrete random variable obtained via a mixture of two geometric random variables (only negative). Strictly speaking, the asymptotic distribution as such does not exist. The cases n even and n odd must be treated separately with two different limiting distributions arising.

Because of this fact the following sequence of statistics is adapted [7]

$$[\frac{L(S^n)}{n} - \frac{1}{2}] + \frac{2}{9}.$$

Here

$$\frac{n}{2} + \frac{r}{18}.$$

These statistics, which take only integer values, converge in distribution to the random variable. This limiting distribution is skewed to the right.

while $P(X=0) =$

$$\frac{1}{2}, \text{ for } k = 1, \dots,$$

$$) = \frac{1}{2}$$

for $k = -1; -2; \dots$

$$P(T = k) = \frac{1}{2^{2|k|+1}}. \tag{9}$$

It follows from (8) that

$$P(T \leq S > 0) = \frac{1}{3 \cdot 2^{-2k}}$$

$$\frac{1}{2^{2|k|-1}}.$$

So the P -value corresponding to the observed value T_{obs} can be evaluated in the following way. Let $U = |T_{\text{obs}}|$.

$$\frac{1}{2^{-2U}} = \frac{1}{2^{-2}}$$

0 1 K

K

which, under the randomness hypothesis, has an approximate distribution

Specifically, for i_1, \dots, i_U running through the set of all 2^U possible vectors of length U , let n_{i_1, \dots, i_U} denote the frequency of the pattern (i_1, \dots, i_U) in the "circularized" string of bits $(i_1, \dots, i_U, i_1, \dots, i_U)$.

$$\chi^2 = \sum_{i_1, \dots, i_U} \frac{(n_{i_1, \dots, i_U} - \frac{2^U}{2^U})^2}{\frac{2^U}{2^U}} = \sum_{i_1, \dots, i_U} \frac{n_{i_1, \dots, i_U}^2}{2^U} - \frac{2^U}{2^U}.$$

Thus, χ^2 is a χ^2 -type statistic, but it is a common mistake to assume χ^2 -distribution. Indeed, the frequencies n_{i_1, \dots, i_U} are dependent.

The corresponding generalized serial statistics for the $(t-1)$ -th order are

$$S_U^{(t)} = \sum_{i_1, \dots, i_U} \frac{(n_{i_1, \dots, i_U} - \frac{2^U}{2^U})^2}{\frac{2^U}{2^U}} = \sum_{i_1, \dots, i_U} \frac{n_{i_1, \dots, i_U}^2}{2^U} - \frac{2^U}{2^U}.$$

=

$$P = \frac{2}{2^U} = \frac{2}{2^U}.$$

For

References

Goodall (1953), "The serial test for random numbers and its application to the Voss test," Cambridge Philosophical Society, 276-284.

at 9f a

1

When n is large, $ApEn(m)$ and its modified version can differ much.
 Indeed, one has with $\frac{1}{Q} \ll \frac{1}{m} \ll \frac{1}{Q}$

TPe test is based on tPe limiting distribution of tPe maximum of tPe absolute values of partial sums, $\max_{1 \leq k \leq n} R_k$

Tim

$$\begin{matrix} k = -1 \\ 1 \end{matrix}$$

$$< (4 \times 3) \rangle :$$

$$k = -1$$

The following is used for the evaluation of the

$$Z = \max_k (\quad) =$$

The test rejects the randomness hypothesis immediately if J is too small, i.e., if the following P -value is small:

$$P(J < J(\text{obs})) = \frac{2}{\pi} \int_0^{J(\text{obs})/\bar{n}} e^{-u^2/2} du = \mathbf{P} \left[\frac{1}{\sqrt{2}} \chi^2_{(1)} \leq \frac{J(\text{obs})}{\bar{n}} \right];$$

If $J < U_{\alpha}(0.005)$

$s(x)$ of the number S of visits to the state x during J excursions which occur on the string. So $s(x) = \sum_{j=1}^J s_j(x)$ where $s_j(x) = 1$ if the number of visits to x in the j th excursion is exactly equal to s , and $s_j(x) = 0$ otherwise. Pool the values of $s(x)$ into classes, say, $S = 0, 1, \dots, 4$ with an additional class ≥ 5 . The theoretical probabilities for these classes are:

$$p_0(x) = P(S = 0; x)$$

$$\frac{1}{4}$$

$$p_0(x) \quad p_1(x) \quad p_2(x) \quad p_3(x) \quad p_4(x) \quad p_5(x)$$

$$s(x) =$$

$$2jxj$$

4. TESTING STRATEGY AND RESULT INTERPRETATION

Three topic areas will be addressed in this section: (1) strategies for the statistical analysis of a random number generator, (2) the interpretation of empirical results using the NIST Statistical Test Suite, and (3) general recommendations and guidelines.

4.1 Strategies for the Statistical Analysis of an RNG

In practice, there are many distinct strategies employed in the statistical analysis of a random number generator. NIST has adopted the strategy outlined in Figure 1. Figure 1 provides a structural illustration of the five stages involved in the statistical testing of a random number generator.

Stage 1: Selection of a Generator

Select a hardware or software based generator for evaluation. The generator should produce a binary sequence of 0's and 1's of a given length. Examples of pseudorandom generators (PRNGs) include Linear Shift Register (LSR), and the Diehard suite (see [10]), and the Xorshift (see [11]).

Stage 2: Binary Sequence Generation

For a fixed sequence of test sequences, save the sequences to a file.

Stage 3: Execute the Statistical Test Suite

be applied.

sequence length. Select the statistical tests and relevant input parameters (e.g., block length) to be used. The NIST Statistical Test Suite using the file produced in Stage 2 and the desired

statistics, and *P-values* for each statistical test. Based on these *P-values*, a conclusion regarding the quality of the sequence generated by the test suite with relevant intermediate values, such as test

Stage 5: Assessment: Pass/Fail Assignment

⁷ Sample data may also be obtained from George Marsaglia's *Random Number CDROM*, at <http://stat.fsu.edu/pub/diehard/cdrom/>.

Figure 1: Architecture of the NIST Statistical Test Suite

For each statistical test, a set of *P-values* (corresponding to the set of sequences) Q_s is produced. For a fixed significance level α , *P-values* are expected to indicate failure. For example, if the significance level α is chosen to be 0.01 (i.e. $\alpha = 0.01$), then about 1 % of the sequences are expected to fail. A sequence passes a statistical test whenever the value α

$l - \hat{p}$), where \hat{p} T Tf 0.012 Tc -0.012 Tw (= 1-) Tj 19.8 0 TD /F8 12 Tf -0.252 Tc 0 Tw (a) Tj 7.32 0 TD /Fw (T Tf -0.0

confidence interval is

$$\pm = .99 \pm \sqrt[3]{.99^{(1)}/1000} \text{ (i.e., } 0.0094392)$$

the proportion should lie about 0.9805607. TPIs can be illustrated using a graph as shown in Figure 2. The confidence interval was calculated using a normal distribution as an approximation to the

binomial distribution, wPich is reasonably accurate for Target sample sizes (e.g., $V \geq$

and fails otherwise. For each statistical test, the proportion of sequences that pass is computed and analyzed accordingly. More in-depth analysis should be performed using additional statistical procedures (see Section 4.2.2).

igamc(

$c = \sum_{i=1}^{10} \frac{2^{-F_i}}{10^s}$, where F_i is the number of *P-values* $0 \leq F_i \leq 0.004$.

(b) An underdeveloped (immature) statistical test.

There are occasions when either probability or complexity theory isn't sufficiently developed or understood to facilitate a rigorous analysis of a statistical test.

Over time, statistical tests are revamped in light of new results. Since many statistical tests are based upon asymptotic approximations, careful work needs to be done to determine how good an approximation is.

(c) An improper implementation of a random number generator.

It might be plausible that a hardware RNG or a software RNG has failed due to a flaw in the design or due to a coding implementation error. In each case, careful review must be made to rule out this possibility.

(d) Improperly written codes to harness test input data.

Another area that needs to be scrutinized is the harnessing of test data. The test data produced by a (P)RNG must be processed before being used by a statistical test. For example, processing might include dividing the output stream from the (P)RNG into appropriate sized blocks, and translating the 0's to negative ones. On occasion, it was determined that the failures from a statistical test were due to errors in the code used to process the data.

(e) Poor mathematical routines for computing P-values

Quality math software must be used to ensure excellent approximations whenever possible. In particular, the incomplete gamma function is more difficult to approximate for larger values of the constant. Eventually, P -value formulas will result in bogus values due to difficulties arising from numerical approximations. To reduce the likelihood of this event, NIST has prescribed preferred input parameters.

(f) Incorrect choices for input parameters.

In practice, a statistical test will not provide reliable results for all seemingly valid input parameters. It is important to recognize that constraints are made upon tests on a test-by-test basis. Take the Approximate Entropy Test, for example. For a

Sequence Length

The determination as to how long sequences should be taken for the purposes of statistical testing is difficult to address. If one examines the FIPS 140-1 statistical tests, it is evident that sequences should be about 20,000 bits long.

However, the difficulty with taking relatively short sequence lengths is problematic in the sense that some statistical tests, such as Maurer's Universal Statistical Test, require extremely long sequence lengths. One of the reasons is the realization that asymptotic approximations regarding the distribution for certain test statistics are more difficult to address for short lengths.

The issue of sample size is tied to the choice of significance level. NIST recommends that, for these tests, the user should fix the significance level to be at least 0.001, but no larger than 0.01^8 . A sample size that is proportional to the significance level may not be suitable. For example, if the significance level is chosen to be 0.001, then it is expected that 1 out of every 1000 sequences will be rejected. If a sample of only 100 sequences is selected, it would be rare to observe a rejection. In the limit ($n \rightarrow \infty$). That is, for a level of 0.001, a sample should have at least 1000 sequences. Ideally, many distinct samples should be analyzed.

Block Size

Block sizes are dependent on the individual statistical test. In the case of Maurer's Universal Statistical test, block sizes range from 1 to 16. However, for each specific block size, a

Intuitively, it would seem that the larger the block size, the more information would be gained from the parsing of a sequence, such as in the Approximate Entropy test. However, a block size that is too large should not be selected either, for otherwise

Template

Certain statistical tests are suited for detecting global non-randomness. However, other statistical tests are more apt at assessing local non-randomness, such as tests developed to detect the presence of m -bit patterns in a sequence. Still, it makes sense that templates of a block size greater than $\lfloor \log_2 n \rfloor$ should not be chosen, since frequency counts will most probably be in the neighborhood of zero, which does not provide any useful information. Thus, appropriate choices must be made.

Other Considerations

In principle, there are many commonly occurring questions regarding randomness testing. Perhaps the most frequently asked question is, *How many tests should one apply?* In practice, no one can truly answer this question. The belief is that the tests should be independent of each other as much as possible.

Another, frequently asked question concerns the need for applying a monobits test. Keep in mind that there will be instances when a finite binary sequence will pass Maurer's test, null hypothesis

Given the uniformly distributed p

This section describes tPe set-up and proper usage of tPe statistical tests developed by NIST tPat are available in tPe NIST test code. Descriptions of tPe algorithms and data structures tPat were utilized are included in tPis section.

5.1 About tPe Package

This tPe package was specifically designed for individuals interested in conducting statistical tests in the phase of the project. It also contains implementations of PRNGs utilized during the development.

Client: The test code was developed using the SUN workstation under the Solaris PRNGs. The code is available from the NIST tPe PRNGs. The file INCLUDE_GENERATORS.c can be found in tPe defs.h header file.

This package will address the problem of evaluating (P)RNGs for randomness. It will be useful in:

+

5.2 System Requirements

This software package was developed on a SUN workstation under the Solaris operating system. All of the source code was written in ANSI C. Source code porting activities were successful for the SGI Origin (IRIX 6.5 with the SGI C compiler) and a desktop computer (IBM PC under Windows 98 and Microsoft C++ 6.0).

In practice, minor modifications will have to be introduced during the porting process in order to ensure the correct interpretation of tests. In the event that a user wishes to compile and execute the code on a different platform, sample data and the corresponding results for each of the statistical tests have been provided. In this manner, the user will be able to gain confidence that

randWm number generatWrs. These include Blum-Blum-Shub, Cubic Congruential GeneratWr, the FIPS 186 one way function based on SHA-1 (G-SHA-1), Linear Congruential GeneratWr, Modular Exponentiation, Micali-SchVWrr, Quadratic Congruential GeneratWr I and II, and Exclusive OR. Code fWr the ANSI X9.17 generatWr and the FIPS 186 one way function based on DES (G-DES) were removed frWm the package because of possible expWrt issues. User defined PRNGs should be copied into this subdQrectWry, with the corresponding modQfications tW ~~the~~ *makefile*, *utilities1.c*, *defs.h*, and *prWtW.h* files.

- The **include/** subdQrectWry contains the header files fWr the statistical tests, pseudo-randWm number generatWrs, and associated rWutines.

5.4 Data Input and Output of Empirical Results

5.4.1 Data Input

Data input may be supplied in one of two ways. If the user has a stand-alone program or hardware device which implements a RNG, the user may want to construct as many fQles of arbitrary length as desired. FQles should contain binary sequences stored as either ASCII characters consisting of zeroes and ones, or as hexadecimal characters stored in binary format. These fQles can then be independently examined by the NIST Statistical Test Suite.

In the event that storage space is a problem, the user may want to modify the reference implementation and plug-in their implementation of the PRNG under evaluation. The binary streams will be stored directly in the *psiTondata* structure, which contains binary sequences.

5.4.2 Output of Empirical Results

The output of empirical results will be stored in two fQles, *tests* and *results*, that correspond respectively to the computational information, e.g., test statistics, intermediate parameters, and *P-values* for each statistical test applied to a data set.

If these fQles are not properly created, then it is most probably due to the inability to open the fQles for output. See Appendix J for further details.

5.4.3 Test Data FQles

Four sample fQles have been created and are contained in the *data/* subdirectory. Four of these fQles correspond to the Mathematica⁹ generated binary expansion of several classical numbers for over 1,000,000 bits. These fQles are *data.e*, *data.pi*, *data.sqrt2*, and *data.sqrt3*. The Mathematica program used in constructing utilizing the SHA-1 hash function.

5.5 Program Layout

The test suite package has been designed to perform statistical tests, (pseudo)random number generation, and data.

The three primary components of the

⁹ **Mathematica**, Stephen Wolfram's Computer Algebra System, <http://www.mathematica.com>.

components include the source code library files, the data directory and the hierarchical directory (**experiments/**) containing the sample data files and empirical result logs, respectively.

5.5.1 General Program

The NIST test suite contains sixteen tests which will be useful in studying and evaluating the binary sequences produced by random and pseudo random number generators. As in previous work in this field, statistical tests must be devised which, under some hypothesized distribution, employ a particular test statistic, such as the number of runs of ones or the number of times a pattern appears in a bit stream. The majority of the tests in the test suite either (1) examine the distribution of zeros and ones in some fashion, (2) study the harmonics of the bit stream utilizing spectral methods, or (3) attempt to detect patterns via some generalized pattern matching technique on the basis of probability theory or information theory.

5.5.2 Implementation Details

In practice, any number of problems can arise if the user executes this software in uncharted domains. It is plausible that sequence lengths well beyond the testing procedure (i.e., on the order of 10^6) may be chosen. If memory is available, there should not be any reason why the software should fail. However, in some instances, user defined limits are prescribed for data structures and workspace. Under these conditions, it may be necessary to increase certain parameters, such as the `MAXNUMOFTEMPLATES` and the `MAXNUMBEROFCYCLES`. Several parameters that may be modified by a user are listed in Table 3.

The parameter *ALPHA* denotes the significance level that determines the region of acceptance and rejection. NIST recommends that *ALPHA* be in the range $[0.001, 0.01]$.

The parameter *ITMAX* is utilized by the special functions; it represents the maximum number of iterations allowed for iterative computation.

The parameter *KAPPA* is utilized by the *gcf* and *gs* routines described in the source file. It represents the desired accuracy for the incomplete gamma function.

The parameter *MAXNUMOFTEMPLATES* indicates the maximum number of templates that may be executed by the Nonoverlapping Template Matching Test of size $m = 9$, up to 148 possible non-periodic templates may be used.

The parameters *NUMOFTESTS* and *NUMOFGENERATORS* represent the maximum number of tests that may be defined in the test suite, and the maximum number of generators specified in the test suite, respectively.

Lastly, the *MAXNUMBEROFCYCLES* represents the maximum number of cycles anticipated in any particular binary sequence.

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5.5.3.3 Mathematical Software

Special functions required by the test suite are the *incomplete gamma function*, the *complementary error function*. The *cumulative distribution function*, is also required, but it can be expressed in terms of the *normal function*.

One of the initial concerns regarding the development of the reference dependencies that were required in order to gain reliable mathematical functions required in the statistical tests. To resolve this matter, the following libraries:

[The Fast Fourier Transform \(FFT\) was obtained at](#)

The normal function utilized in this code was expressed in terms of the error function.

Standard Normal (Cumulative Distribution) Function

| STATISTICAL TESTS | | |
|----------------------|---------------------------|--------------------|
| [01] Frequency | [02] Block Frequency | [03] Spectral - DC |
| [03] Cumulative Sums | [04] Longest RuVs of Ones | [05] Spectral - DC |

In this case, 0 has been selected to indicate interest in applying a subset of the available statistical tests. The following screen is then displayed.

As shown above, the only test applied was number 9, the Nonoverlapping templates test, a query for the desired sample size Q_s then made.

Ten sequences will be parsed using the `data.parse_sequences` function. A subsequent query will specify whether the file consists of bits stored in ASCII format or binary format.

Apply elementary row operations where the addition operator is taken to be the exclusive-OR operation. The matrices are reduced to upper triangular form using forward row operations, and the operation is repeated in reverse in order using backward row operations in order to arrive at a matrix in triangular form. The rank is then taken to be the number of nonzero rows in the resulting Gaussian reduced matrix.

Forward Application of Elementary Row Operations:

Let each element in the m by m matrix be designated as $a_{i,j}$

1. Set $i = 1$
2. If element $a_{i,i} = 0$, (i.e., the element on the diagonal $\neq 1$), then swap all elements in the i^{th} row with all the k^{th} row, where $a_{k,i} = 1$
3. If element $a_{i,i} \neq 1$, then divide all elements in the i^{th} row by $a_{i,i}$

2. If element $a_{i,i} = 0$ (i.e., the element on the diagonal $\neq 1$), then swap all elements in the i^{th} row with all elements in the next row that contains a one in the i^{th} column (i.e., the row is the k^{th} row, where $k \leq S < i$). If no row contains a "1" in the i^{th} position, go to step 4.
3. If element $a_{r_{ww}, col} = 0$, then go to step 3g.
- d.

| | | |
|---|--------|------------------------|
| | 000010 | |
| | 100000 | |
| | 000001 | |
| | 001010 | Since $a_{3,3} \neq 1$ |
| D | 000001 | |
| | 001011 | |
| | 000010 | |

| | | |
|---|--|--|
| | 0 0 0 0 0 1 | |
| J | 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 | Since $a_{4,4} = 1$ and no other row has a 1 in column 4, the matrix is not altered. |
| K | 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 0 0 0 0 0 0 0 1 0 0 0 0 0 0 1 | Since $a_{3,3} = 1$, but no other row has a 1 in column 3, the matrix is not altered. |

Filename: *defs.h*

introduced under tPe realization that underlying libraries may not be available on all platforms. TPe user can disable tPe sample generators and shWuld disable statistical tests.

Lines 2-4 refer to different probability values tPat have been included in the Test. Since tPe statistical test partitions a sequence into sub-strings, tPe has tPe freedom to select between several cases. TPe user shWuld be able to disable the otPer two cases.

Lines 5-7 refer to tPe ability to store intermediate paralibter values.

corresponding moduli into tPe files, *fourierPoints* and *magnitude*, enable or disable tPe storage of the sequence lengthP and approxQmum sequence lengthPs into tPe files, *abscissaValues* and *ordinateValues*, tPe kHf of tPe number of cycles for eacP binary sequence into tPe kHf.

s to tPe number of sequence lengthP step increments to be taSen during tPe generation of tPe approxQmate entropy values in tPe file *ordinateValues*.

Filename: *defs.h*

Global Constants:

1. #define ALPHA
2. #define MAXNUMOFTEMPLATES

0.01

Template MatcPing test.

L i n e 3 r e f e r s t o t P e m a x Q m u m number of additional tests, tPis paralibter shWuld be incremented.

Line 4 refers to tPe maxQmum number of generators, tPis paraleter shWuld be incremented.

number is insufficient, the user may increase the parameter `appro`

LQne 6 refers to the maximum number of files which may be decomposed. This route is applied only for `partQtQonResultFile`. *P-value* is produced per sequence. This route decomposes the separate files, *data001*, *data002*, *data003*, ...

APPENDIX C: EMPIRICAL RESULTS FOR SAMPLE DATA

The user is urged to validate that the statistical test suite is operating properly. Five sample files have been provided. These five files are: (1) *data.random*, (2) *data.shuffled*, (3) *data.sha1*, (4) *data.sqrt2*, and (5) *data.sqrt3*. For each data file, the following tests were applied, and the results recorded in the following tables. The tests include: Frequency of Ones, Non-overlapping Template Matching, Overlapping Template Matching, Approximate Entropy, Linear Complexity and Serial tests require parameters. The exact values used in these examples has been included in the name of the statistical test. In the case of the random excursions test, the parameters are 18 and 18.

Example #1: The binary expansion of π

| Statistical Test | P-value |
|-------------------------------|--|
| Frequency | 0.578211 |
| Block Frequency ($n = 100$) | Random Excursions Variant ($x = -1$) |

| | |
|------------------------------|----------|
| Lempel-Ziv Complexity | 0.311710 |
| Serial ($n = 5, \nabla^2$) | 0.583812 |

Example #2: The binary expansion Wf e

| Statistical Test | P-value |
|---|----------|
| Frequency | 0.953749 |
| Block Frequency ($m = 100$) | 0.619340 |
| Cusum-Forward | 0.669887 |
| Cusum-Reverse | 0.724266 |
| Runs | 0.561917 |
| Long Runs Wf Ones ($M = 10000$) | |
| Rank | 0.306156 |
| Spectral DFT | 0.443864 |
| NonOverlapping Templates ($m = 9, B = 0000000010$) | |
| Overlapping Templates ($m = 9$) | 0.110434 |
| Universal ($L = 7, Q = 1280$) | 0.282568 |
| ApproxQmate Entropy ($n = 5$) | 0.361688 |
| Random Excursions ($x = +1$) | 0.778616 |
| Random Excursions Variant ($x = -1$) | 0.826009 |
| Lempel Z(U Complexity) Tj 326.64 0 TD 0 Tc 0 Tw (0.004 0.22) Tj ET 66.36 491.28 0.48 0.48 re f 66.84 491.28 | |
| Serial ($m = 5, \nabla \Psi_v^2$) | 0.225783 |

Example #3: A G-SHA-1 binary sequence

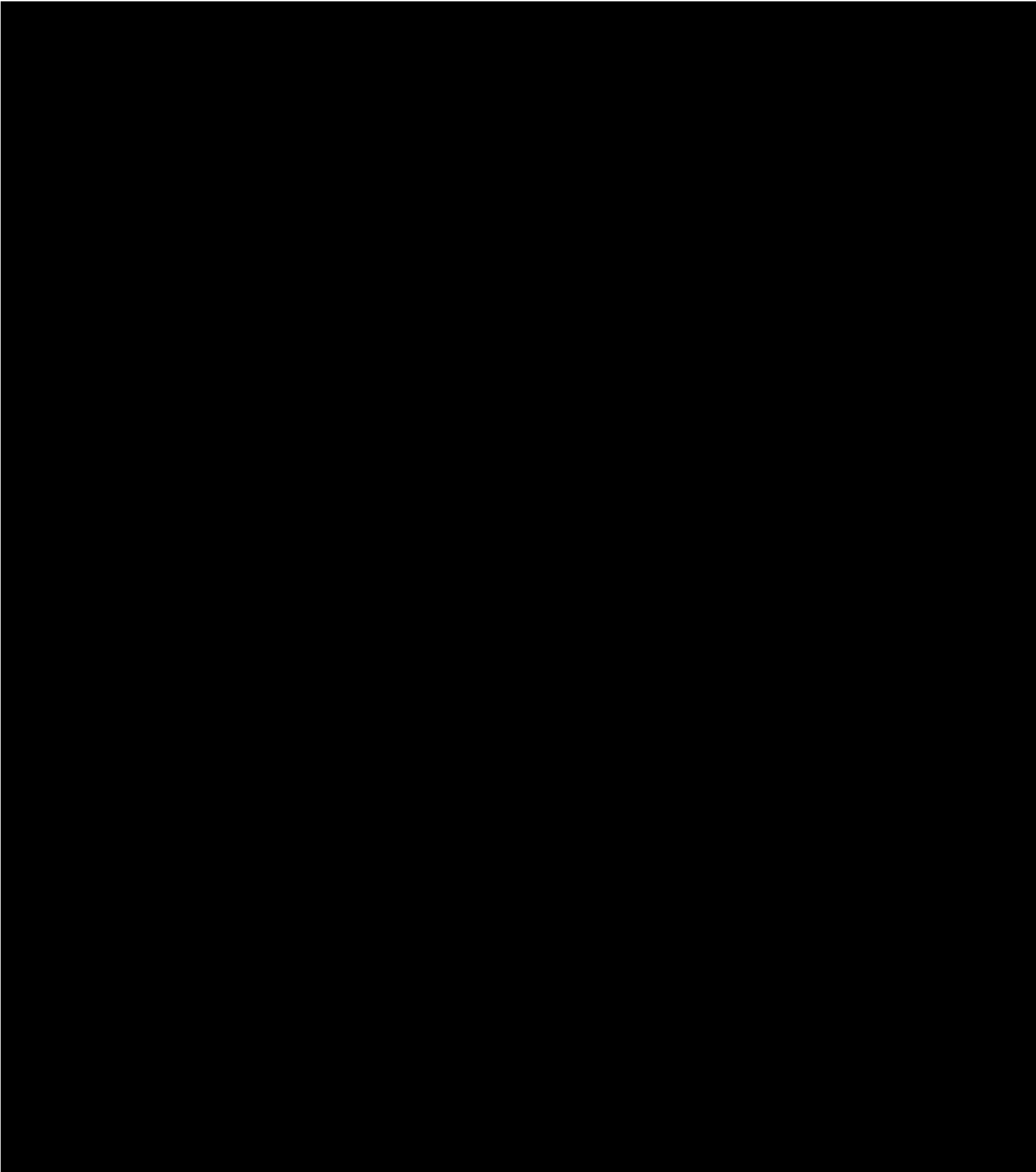
Random Excursions Variant (

| Statistical Test | P-value |
|---|----------|
| Frequency | 0.604458 |
| Block Frequency ($m = 100$) | 0.833026 |
| Cusum-Forward | |
| Cusum-Reverse | 0.550134 |
| Runs | 0.309757 |
| LoVg Runs Wf Ones ($M = 10000$) | 0.657812 |
| Rank | 0.577829 |
| Spectral DFT | 0.086702 |
| NoVOverlappiVg Templates ($m = 9, B = 000000001$) | |
| OverlappiVg Templates ($m = 9$) | 0.339426 |
| Universal ($L = 7, Q = 1280$) | 0.411079 |
| Random Excursions ($x = +1$) | 0.000000 |

Lempel Z(U Complexity) Tj 326.64 0 TD 0 Tc 0 Tw (0.398475) Tj ET 66.36 200.52 0.48 0.48 re f 66.84 200.52

Example #4: The binary expansion of $\sqrt{2}$

| Statistical Test | P-value |
|---|----------|
| Frequency | 0.811881 |
| BlWck Frequency ($n = 100$) | 0.289410 |
| Cusum-Forward | 0.879009 |
| Cusum-Reverse | 0.957206 |
| Runs | |
| Spectral DFT | 0.267174 |
| NonOverlapping Templates ($m = 9, B = 000000001$) | 0.569461 |
| Overlapping Templates ($f = 0, 1982$) | |
| UnQversal ($L = 7, Q = 1280$) | 0.130805 |
| Approximate Entropy ($m = 5$) | 0.853227 |




```

void displayBits(FILE* fp, long value, long count)
{
    int i, j, match, c, displayMask = 1 << (B-1);
    fWr(i = 0; i < B; i++) A[i] = 0;
    fWr if (value &= displayMask)

```

```

        A[c-1] c ;
    else

```

```

    fWr(i c ; i < count; i++) {
        match = 1;
        if ((A[B-count] != A[B-1]) &&
            ((A[B-count] != A[B-2]) || (A[B-count+1] != A[B-1]))) {
            Qf (A[c] != A[c+i]) {
                match = 0;
                break;
            }
        }
        Qf (match) {
            /* printf("\nPERIODIC TEMPLATE: SHIFT = %d\n",i); */
            break;
        }
    }
    if (!match) {
        fWr(c = B-count; c < (B-1); c++) fprintf(fp,"%u",A[c]);
        fprintf(fp,"%u\n", A[B-1]);
        return;
        nonPeriodic++;
    }
}

```

The sample Mathematica program utilized in constructing four s

Mathematica Program

```
(*****)
(* Purpose: Converts num to its decimal expansion using *)
(*           its binary representation. *)
(*           *)
(* Caution: The $Max precision variable must be set to *)
(*           the value of d. By default, Mathematica *)
(*           sets this to 50000, but this can be increased. *)
(*****)
```

```
BinExp[num_,d_] := Module[{n,L},
    If[d > $Max precision, $Max79precision = d];
    n = N[num,d];
    L = First[RealDigits[n,2]]
];
```

```
Save["data.e",{SE}];
```

```
Save["data.pi",{SP}];
```

```
Save["data.sqrt2",{S2}];
```

```
Save["data.sqrt3",{S3}];
```

For each binary sequence, an individual statistical test must produce at least one *P-value*. *P-values* are based on the evaluation of special functions, which must be as accurate as possible on the target platform. The *P-values* produced by each statistical test, report *P-values* with six digits of precision, which should be sufficient. However, if greater precision is desired, modify the *printf* statements in each statistical test accordingly.

During the testing phase, NIST commonly evaluated sequences on the order 10^6 ; hence, results are based on this assumption. If the user wishes to choose longer sequence lengths, then be aware that numerical computations may be inaccurate¹⁴ due to machine or algorithmic limitations. For further information on numerical analysis matters, see [6]¹⁵.

For the purposes of illustration, sample parameter values and corresponding special function values are shown in Table F.1 and Table F.2. Table F.1 compares the results for the incomplete gamma function for selected parameter values for a and x . The results are shown for Maple¹⁶, Matlab, and the Numerical Recipe¹⁷ routines. Recall that the definitions for the *gamma function* and the *incomplete gamma function* are the following, respectively, as:

$$\text{where } \Gamma(a, 0) = 1 \text{ and } \Gamma(a, \infty) = 0.$$

The algorithm used in the test suite implementation of the *incomplete gamma function* is the Numerical recipe codes, it is evident that the function is accurate to at least the decimal place. For large values of a , the precision will degrade, as will confidence in the test. A computer algebra system is employed to ensure high precision computations).

Table F.2 compares the results for the *complementary error function* (see Section 5.3.3) for parameter values for x . The results are shown for ANSI C, Maple, and Matlab. Recall the definition for the *complementary error function* is:

$\overline{\mathcal{T}}$

| | | | |
|-------------|--------------|-------------|----------|
| a1= x = 600 | | a = x = 800 | $Q(a,x)$ |
| MapTe | 0.4945710333 | MapTe | |
| Test Suite | 0.4945710331 | Test Suite | |

rng/

makefile The NIST Statistical Test Suite *makefile*. This file is invoked in order to recompile the entire test suite, including PRNGs.

makefile2 The NIST Statistical Test Suite

event that the user Qs Qnterested Qn evaluating their PRNG (online), their source code Uay, for example, be added as *generators4.c* Qn thQs directory, with additional changes Uade Qn the *utilities2.c* file and the *defs.h* file.

generators1.c: contains BBS, MS, LCG

generators2.c: contains ModExp, QCG1, QCG2, CCG1, XOR

generators3.c: contains G-SHA-1

sha.c : contains routines required by the G-SHA-1 PRNG.

ThQs file contains bi

universal.o

utilities1.o

This subdirectory contains tPe templates (or patterns) which are evaluated in tPe NonOverlapping Template Matching Test. TPe corresponding file is opened for tPe prescribed template blWck length m . CurrentTy, tPe onTy options for which nonperiodic templates have been stored are tPose which lie in [2,21]. In tPe e Tw nt tDat > 21, tPe user must pre-compute tPe non-periodic templates.

| | | | | |
|------------|------------|------------|------------|------------|
| template2 | template3 | template4 | template5 | template6 |
| template7 | template8 | template9 | template10 | template11 |
| template12 | template13 | template14 | template15 | template16 |
| template17 | template18 | template19 | template20 | template21 |

There are several visualization approaches that may be used to investigate the randomness of binary sequences. Three techniques involve the Discrete Fourier Transform, approximate entropy and the Linear complexity profile.

(a) Spectral - Discrete Fourier Transform (DFT) Plot

Figure H.1 depicts the spectral components (i.e., magnitude of the DFT) obtained via application of the *Fast Fourier Transform* on a binary sequence (consisting of 5000 bits) extracted from the Blum-Blum-Shub pseudo-random number generator¹⁸. To demonstrate how the spectral test can detect periodic features in the binary sequence, every 10th bit was changed to a single one. To pass this test, no more than 5 % of the peaks should surpass the 95 % cutoff, (determined to be $\sqrt{3 \cdot 5000} \approx 122.4744871$). Clearly, greater than 5 % of the peaks exceed the cutoff point in the figure. Thus, the binary sequence fails this test.

Figure H.1 Discrete Fourier Transform Plot

¹⁸ The Blum-Blum-

(b) Approximate Entropy (ApEn) Graph

Figure H.2 depicts the approximate entropy values (for block length = 2) for three binary sequences, the binary expansion of e and π , and a binary sequence taken from the SHA-1 pseudo-random number generator. In theory, for an n -bit sequence, the maximum entropy value that can be attained is $\ln(2) \approx 0.69314718$. The x-axis reflects the number of bits considered in the sequence. The y-axis reflects the deficit from maximal QrruguTarity, that is, the difference between the $\ln(2)$ and the observed approximate entropy value. Thus, for a fixed sequence length, one can determine which sequence appears to be more random. For a sequence of 1,000,000 bits, e appears more random than both π and the SHA-1¹⁹ sequence. However, for larger block sizes, this is not the case.



Figure H.2: Approximate Entropy Graph

¹⁹ It is worth noting that, for larger block sizes and sequence lengths on the order of 10^6 , SHA-1 binary sequences yield deficit values on the order of 10^{-9} .

(c) LQnear Complexity Profile

Figure H.3 depicts the LQnear complexity profile for a pseudo-random number generator that is strictly binary and the XOR (exclusive-or) operation. The generator is defined as follows according to

$$\text{the rule, } x_i = x_{i-127} \oplus x_i \text{ for } i \geq 128.$$

The Berlekamp-Massey²⁰ algorithm computes the connection polynomial that, for some seed value, reconstructs the finite sequence. The degree of this polynomial corresponds to the length of the shortest LQnear Feedback Shift Register (LFSR) that replicates the polynomial. The LQnear complexity profile depicts the degree, which for a random finite length sequence is about $n/2$. Thus, the x-axis reflects the number of bits observed on the sequence thus far. The y-axis depicts the degree of the connection polynomial. At $n = 254$, observe that the degree of the polynomial ceases to increase and remains constant at 127. This value precisely corresponds to the number of bits on the seed used to construct the sequence.

: LQnear Complexity Profile

²⁰ For a description of the algorithm see Chapter 6 - Stream Ciphers, which may be accessed at <http://www.ca.f4.math.uwaterloo.ca/hac/>.

APPENDIX I: STATISTICA

In order to add another statistical test to the test suite, the user should make the following modifications:

- 1.[In the file **include/defs.h**

Insert any test input parameters into the **testParameters** structure.
of **NUMOFTESTS** by the Vumber of tests to be added.

2. [In the `include/` proto.h]

Insert the statistical test function prototype de

3. [In the file `src/utilities1.c`]

Embed the test function call into the `nist_test_suite`.
current Number of tests is 16, and one test is to be

```
if ((testVector[0] == 1) ||
    myNewTest(tp.myNewTestI
```

- 4.
- src/myNewTest.c]**

Define the statistical test function `stat` and `result` statements using `stat` and `result` statements. The intermediate test “statistic parameters” is used for the tests.

- 5.[In `thesrc/utfiles2.c`]

(openOutputStreams, insert the **testNames** variable. In the function, **chooseTests**, insert the following lines of code modified by the actual Vumber of total tests):

```
printf("\t\t\t\t\t 12345*7891111111\n");  
printf("\t\t\t\t\t      012345*7\n");
```

Note: For each PRNG defined in the package, a sub-directory **myNewTest** must be created.

- (b) In the 1990s, the Vumber

```
printf("    [17] My New Test\n");
```

(c) If an input test parameter is required, in the function, **fixParameters**, insert the following lines of code (under the assumption that **UyNewTestParameter** is an integer. For example, if the total Number of tests is 17, insert

```
stVector[17] == 1) {  
MyNewTest Parameter Value:  ");  
UyNewTestParameter);
```

In order to add a PRNG to the test suite, the user should make the following modifications:

- 1.

```
char generatorDir[20][20] = {"AlgorithmTesting/",  
                             ..., "XOR/", "MYNEWPRNG/"};
```

SimilarTy, in the routine **partitionResultFile**, in the file, *assess.c*.

K.1 Introduction

A simple Tcl/Tk graphical user interface (GUI) was developed as a front-end to the NIST

battery of statistical tests. This will result in the de-iconification of the GUI. Upon completion, the GUI will re-iconify. The user should then proceed to review the file *finalAnalysisReport.txt* to assess the results.

K.2 An Example

The following table presents an example of the use of the GUI. The user has checked all sixteen of the statistical tests and entered:

| | |
|---|---|
| <i>data.e</i> as the binary data stream filename | <ul style="list-style-type: none"> • 9 as the overlapping template block length |
| <ul style="list-style-type: none"> • a sequence length of 1000000 bits | <ul style="list-style-type: none"> • 7 as the universal block length |
| <ul style="list-style-type: none"> • 1 as the number of binary sequences | <ul style="list-style-type: none"> • 1280 as the universal initialization steps |
| <ul style="list-style-type: none"> • 0 as the stream type | <ul style="list-style-type: none"> • as the approximate entropy block length |
| <ul style="list-style-type: none"> • 100 as the block frequency block length | <ul style="list-style-type: none"> • as the serial block length |
| <ul style="list-style-type: none"> • 9 as the nonoverlapping template block length | <ul style="list-style-type: none"> • 500 as the linear complexity substring length |

K.3 Guidance in the Selection of Parameters

Section 2 provides the recommended parameter choices for each statistical test.

K.4 Interpretation of Results

Section 4.2 contains information regarding the interpretation of empirical results.

K.5 Test/Tk Installation Instructions

Test/Tk may be obtained from the Scriptics website at <http://www.Scriptics.com/>

K.6 References

- [1] Brent Welch, Practical Programming in Tcl and Tk, 2nd edition . Prentice Hall PTR, 1997.
- [2] Clif Flyntf, Tcl/Tk for Real Programmers. Academic Press, 1999.

APPENDIX L: DESCRIPTION OF THE REFERENCE PSEUDO RANDOM NUMBER GENERATORS

The NIST Statistical Test Suite supplies the user with nine pseudo-random number generators. A brief description of each pseudo-random number generator follows. The user supplied sequence length determines the number of iterations for each generator.

L.1 Linear Congruential Generator (LCG)

The input parameter for the Fishman and Moore²¹ LCG²² is fixed in code but may be altered by the user.

Input Parameter:

$$z_0 = 23482349$$

Description:

Given a seed z_0 subsequent numbers are computed based on $z_{i+1} = a * z_i \bmod (2^{31}-1)$, where a is a function of the current state. These numbers are then converted to uniform values in $[0,1]$. At each step, output '0' if the number is ≥ 0.5 , otherwise output '1'.

L.2 Quadratic Congruential Generator I (QCG-I)

The input parameters for the QCG-I are fixed in code, but may be modified by the user.

Input Parameters:

$$p = 987b6a6bf2c56a97291c445409920032499f9ee7ad128301b5d0254aa1a9633fdbd378d40149f1e23a13849f3d45992f5c4c6b7104099bc301f6005f9d8115e1$$

$$x_0 = 3844506a9456c564b8b8538e0cc15aff46c95e69600f084f0657c2401b3c244734b62ea9bb95be4923b9b7e84eeaf1a224894ef0328d44bc3eb3e983644da3f5$$

²¹ Fishman, G. S. and L. R. Moore (1986). An exhaustive analysis of multiplicative congruential random number generators with modulus $2^{31}-1$, SIAM Journal on Scientific and Statistical Computation, 7, 24-45.

²² Additional information may be found in Chapter 16 (Pseudo-Random Sequence Generators & Stream Ciphers), Section 16.1 (Linear Congruential Generators) of Bruce Schneier's book, Applied Cryptography: Protocols, Algorithms and Source Code in C, 2nd edition, John Wiley & Sons, 1996.

Description:

Using a 512-bit prime p , and a random 512-bit seed x_0 , construct subsequent elements (each 512-bit numbers) in the sequence via the rule:

$$x_{i+1} = x_i^2 \bmod p, \quad i \text{ f o r}$$

Input Parameter:

x_1 x x

Description:

For a detailed description of SHA1G (the FIPS 186 one-way function using SHA-1), visit <http://www.cacr.math.uwaterloo.ca/hac/about/chap5.pdf> specialType p. 175.

L.8 Blum-Blum-Shub Generator (BBSG)

The input parameters to the BBSG are n and t fixed in code. p and q are variable parameters, which are time dependent. The required parameters are two primes, p and q , and a random integer

s .

Input Parameters: _____

ANSI C reference implementation may be located at <ftp://www.mindspring.com/users/pate/cryptW/chap05/micali.c>.

[1] M.

- [13] MAPLE, A Computer Algebra System (CAS). Available from Waterloo Maple Inc.; <http://www.maplesoft.com>.

