NETWORK TRAFFIC ANOMALY DETECTION USING EMD AND HILBERT-HUANG TRANSFORM

A thesis presented to the faculty of the Graduate School of
Western Carolina University in partial fulfillment of the
requirements for the degree of Master of Science in Technology.

By

Jieying Han

Director: James Z. Zhang, Ph.D.
Dean & Professor
Department of Engineering and Technology

Committee Members:
Dr. Robert Adams, Department of Engineering and Technology
Professor Paul Yanik, Department of Engineering and Technology

April 2013

ACKNOWLEDGEMENTS

Firstly, I am sincerely grateful to all the faculty members of Kimmel School for their assistance and support during the past two years. My gratitude is extended to my committee members Dr. Robert Adams and Professor Paul Yanik for their guidance and encouragement.

I would like to thank Dr. Weiguo Yang, Dr. Julia Barnes, Dr. Michael Smith, Dr. Martin Tanaka and Dr. Steve Ha for their help and advice to my Ph.D. application.

Many thanks go to Jerry Denton, Shawn Lyvers, Nathan Thomas and Michael Jordan for their patience and help during my summer internship. Thanks to Alison Krauss and Pat Smith for their assistance. Also thanks go to my classmates who helped with my study.

My utmost thanks go to my advisor, Dr. James Z. Zhang. Thank you for everything, especially for opening the door of opportunity. Thank you for your encouragement, willingness to help and advice on issues far beyond this degree. You will always be the "King of Advisors" to me.

Finally, best wishes to my family and thanks for their endless support.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

ABSTRACT

NETWORK TRAFFIC ANOMALY DETECTION USING EMD AND HILBERT-HUANG TRANSFORM

Jieying Han, M.S.T.

Western Carolina University (April 2013)

Director: James Z. Zhang, Ph.D.

Empirical Mode Decomposition (EMD) and Hilbert-Huang Transform (HHT) provide a means for adaptive data analysis. EMD extracts Intrinsic Mode Functions (IMFs) that represent the frequency and amplitude characteristics of a signal. HHT generates the marginal spectrum and energy density level of a signal. The IMFs, the marginal spectrum, and the energy density level characterize a signal from three different perspectives.

This thesis proposes three novel parameters for network traffic anomaly detection based on the above three signal characteristics. Hurst parameter of network traffic is calculated based on the first IMF, and is expanded by introducing a weighted self-similarity based on the concept of entropy. Pearson's distance is calculated based on the marginal spectrum to differentiate normal traffic from abnormal ones. Finally, the slopes of cross-correlations are calculated based on the energy density level to detect the rate of energy change between normal and abnormal internet traffic.

CHAPTER 1: INTRODUCTION

Enormous growth of computer network usage and the huge increase in information sharing over the internet have made network security a more and more important field for research. Effective, accurate, and timely detection of network traffic anomaly has become a requirement in the field of information security.

Various schemes are proposed for the network traffic anomaly detection, such as the mode matching approach [1,2], statistical analysis approach [3-8] and Hurst parameter analysis approach [9-11], etc. These approaches have greatly promoted the development of anomaly detection and have improved detection results dramatically. However, due to the complexity of network traffic, no detection model exists that demonstrates both low false positive and low false negative results.

Many researchers have had the idea of using signal processing techniques to detect anomalies in network traffic [12]. Such techniques can detect novel incidents and attacks that cannot be detected by using signature-based approaches. A signature-based approach like Snort® must be updated with new rules in order to recognize new anomalies in network traffic. This means such approaches cannot detect new attacks or zero-day attacks that would not be included in the current rules. Signal processing techniques, on the other hand, could be used to detect such attacks. Examples of signal processing techniques include wavelet analysis, entropy analysis, principal component analysis, and spectral analysis.

J.D. Brutlag introduced time series analysis for detecting aberrant behavior through network monitoring by using the Holt-Winters forecasting algorithm [13]. C. M. Cheng proposed a spectral analysis technique to distinguish between normal TCP network traffic and traffic that was dropped or rate-limited by DoS attacks [14]. M. Thottan used signal processing and an abrupt change detection technique in order to detect several anomalies in IP networks [3]. Moreover, Y. Chen applied spectral analysis to TCP flows so as to defend against reduction of quality attacks [15].

Network traffic entropy analysis has been employed by Y. Gu to detect network traffic anomalies including different kinds of SYN attacks and port scans [16]. A. Wagner used an entropy based method to also detect anomalies and worms propagating in fast IP networks like the Internet backbone [17]. Furthermore, A. Lakhina and B. I. P. Rubinstein used principal component analysis for diagnosing anomalies in network-wide traffic [18,19]. H. Ringberg discussed the sensitivity of the parameters used in principal component analysis for network traffic anomaly detection [20].

Wavelet analysis is a well-studied signal processing technique for detecting anomalies in network traffic. There are many studies that apply wavelet transformations to network traffic. For example, V. Alarcon-Aquino presented an algorithm based on undecimated discrete wavelet transform and Bayesian analysis [21]. This algorithm is able to detect and locate subtle changes in variance and frequency in the given time series. Anu Ramanathan presented a WADeS (Wavelet based Attack Detection Signatures) mechanism based on wavelet analysis to detect the DDoS attack [22], which makes wavelet transform for the traffic signals, then computes the variance of the wavelet coefficients to estimate the attack points. Barford presented a method which decomposes network traffic with decimated discrete wavelet transform, then synthesizes to Low, Mid, High frequency-parts, and finally detects anomaly with Deviation Scoring [23]. This algorithm is able to detect the flash crowds and short-term anomalies in postmortem. Seong Soo Kim proposed a technique for traffic anomaly detection based on analyzing correlation of destination IP addresses in outgoing traffic at an egress router [24]. This technique can be employed for postmortem and real-time analysis of outgoing network. Lan Li proposed an energy distribution based on wavelet analysis to detect the distributed denial-of-service (DDoS) attack [25]. This research showed that the energy distribution variance changes markedly causing a "spike" when traffic behaviors affected by DDoS Attack.

The detection accuracy of these methods is dependent upon the assumption that the network traffic signal $x(t)$ is stationary. However, the stationarity of network traffic is just an assumption and has no strict mathematical proof. Therefore, the methods mentioned above lack reliable theoretical support [26].

EMD is a new data analysis method developed in recent years. Since the decomposition is based on the local characteristics of the data, it is applicable to non-linear and non-stationary processes. EMD and HHT provide a means for adaptive data analysis. EMD extracts Intrinsic Mode Functions (IMF) that represents the frequency and amplitude characteristics of a signal. HHT generates the marginal spectrum and energy density level of a signal. The IMFs, the marginal spectrum, and the energy density level characterize a signal from three different perspectives.

This thesis proposes three novel parameters for internet traffic anomaly detection based on the above three signal characteristics. Hurst parameter of network traffic is calculated based on the first IMF, and is expanded by introducing a weighted self-similarity based on the concept of entropy. Pearson's distance is calculated based on the marginal spectrum to differentiate normal traffic from abnormal ones. Finally, the slopes of cross-correlations are calculated based on the energy density level to detect the rate of energy change between normal and abnormal internet traffic.

The rest of the thesis is organized as follows: Chapter 2 is background theory of HHT method, Hurst's Rescaled-Range(R/S) model and introduction of our testing data. Chapter 3 introduces and explains the three novel detection methods. Chapter 4 illustrates the testing results through the project. The final chapter provides conclusions and future work.

CHAPTER 2: BACKGROUND

2.1 Hilbert-Huang Transform

Hilbert-Huang Transform is a new method for analyzing nonlinear and non-stationary data. The key part of the HHT is the Empirical Mode Decomposition method with which any complicated data set can be decomposed into a finite and often small number of Intrinsic Mode Functions that admit well-behaved Hilbert transforms [27].

2.1.1 Empirical Mode Decomposition Method

The principle of EMD is to decompose a signal into a sum of IMFs. Each IMF should satisfy the following conditions:

1) In the whole data set, the number of extrema and the number of zero-crossings must either equal or differ at most by one.

2) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

The first condition is similar to the traditional narrow band requirements for a stationary Gaussian process. The second condition is new - its locality is necessary so that the instantaneous frequencies will not have unwanted fluctuations induced by asymmetric waveforms [28].

The decomposition process of a signal is an iterative procedure and is described in figure 2.1:

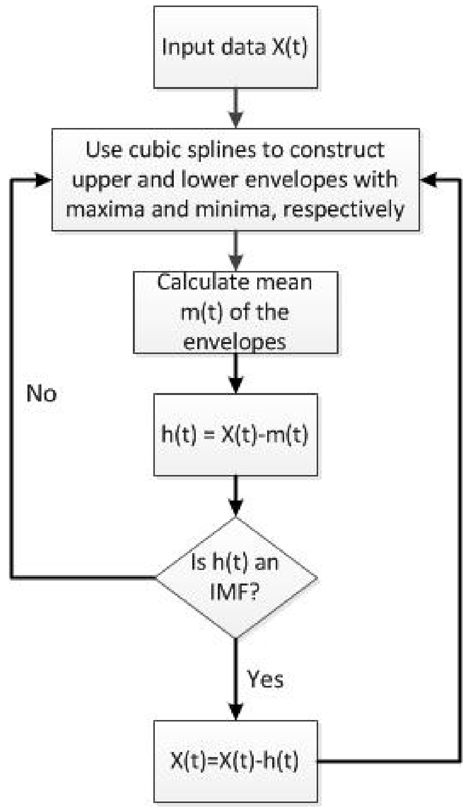


Figure 2.1: EMD Procedures

The EMD procedures can be summarized as follows:

Given a signal $X(t),(t=1,...,T)$

1) Identify all the maxima and minima of $X(t)$.

2) Generate its upper and lower envelopes, $X_{up}(t)$ and $X_{low}(t)$, with spline interpolation.

3) Calculate the point-by-point mean from upper and lower envelopes, $m(t)=[X_{up}(t)+X_{low}(t)]/2$.

4) Subtract the mean of the envelopes from the signal $X(t)$ to obtain a new signal, $h(t)=X(t)-m(t)$.

5) Check the properties of $h(t)$: If $h(t)$ meets the above-defined two conditions, an IMF is derived and replace $X(t)$ with the residual $r(t)=X(t)-h(t)$; If $h(t)$ is not an IMF, replace $X(t)$ with $h(t)$.

6) Repeat Steps 1) - 5) until the residual satisfies given stopping criteria.

At the end of this process, the signal $X(t)$ can be expressed as follows:

$$X(t) = \sum_{i=1}^{n} c_i + r_n \tag{2.1}$$

Components $c_1, c_2 ... c_n$ contain the ingredients from high-frequency to low-frequency of the signal. r_n contains trend information of the original signal.

The stopping criterion can be the Standard Deviation (SD) between two consecutive results in the sifting process. SD can be expressed as the following equation and the simulation results revealed that the reasonable values are between $0.25 \sim 0.3$.

$$SD = \sum_{t=0}^{T} \left[\frac{|h_{i(k-1)}(t) - h_{ik}(t)|^2}{h_{i(k-1)}^2(t)} \right] \tag{2.2}$$

In this approach, we only decompose the signal into one IMF and a residue $(n = 1)$ since the first IMF provides sufficient information to detect the attacks.

2.1.2 Hilbert Spectrum

After applying the EMD, each IMF is an AM-FM component, which can be processed with the Hilbert Transform:

$$\hat{c}_i(t) = \frac{1}{\pi} \int_{-\infty}^{+\infty} \frac{c_i(\tau)}{t - \tau} d\tau \tag{2.3}$$

Where $c_i(t)$ is the i^{th} IMF, and $\hat{c}_i(t)$ is the Hilbert transform of $c_i(t)$. With this definition, $c_i(t)$ and $\hat{c}_i(t)$ form a complex conjugate pair, so we can form the analytic signal of each IMF, $z_i(t)$, as:

$$z_i(t) = c_i(t) + i\hat{c}_i(t) = a_i(t)e^{j\theta_i(t)} \tag{2.4}$$

where

$$a_i(t) = [c_i^2(t) + \hat{c}_i{}^2(t)]^{1/2} \qquad \theta_i(t) = \arctan\left(\frac{\hat{c}_i(t)}{c_i(t)}\right) \tag{2.5}$$

The instantaneous frequency is given by $\omega_i(t) = d\theta_i(t)/dt$, the Hilbert Spectrum of each IMF is defined as:

$$H_i(\omega,t) = a_i(t)e^{j\theta_i(t)} = a_i(t)e^{j\int \omega_i(t)dt} \tag{2.6}$$

2.1.3 Marginal Spectrum

Hilbert marginal spectrum of the i^{th} IMF is defined as:

$$h_i(\omega) = \int_0^T H_i(\omega,t)dt \tag{2.7}$$

where T is the duration of the signal, $h_i(\omega)$ offers a measure of total amplitude (or energy) contribution as a function of frequency, which represents the cumulated amplitude over the entire data span in a probabilistic sense.

2.1.4 Energy Density Level

In addition to the marginal spectrum, the instantaneous energy density level of the i^{th} IMF, IE_i, is defined as:

$$IE_i(t) = \int_\omega H_i^2(\omega,t)d\omega \tag{2.8}$$

IE depends on time, which can be used to check the energy fluctuation. When attacks occur, the energy will change significantly. That's why we choose *IE* as a parameter for detection.

The process of HHT is described as follows:

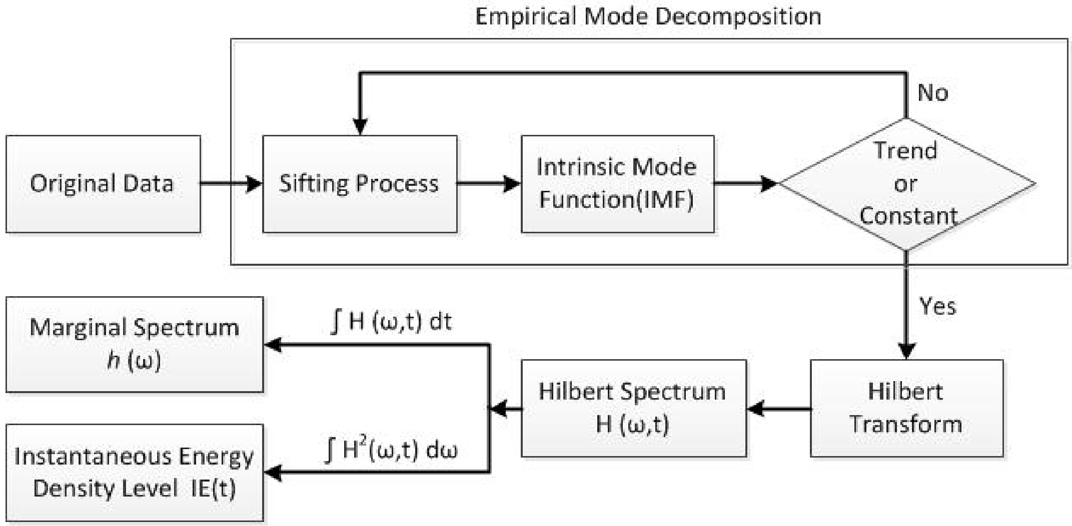


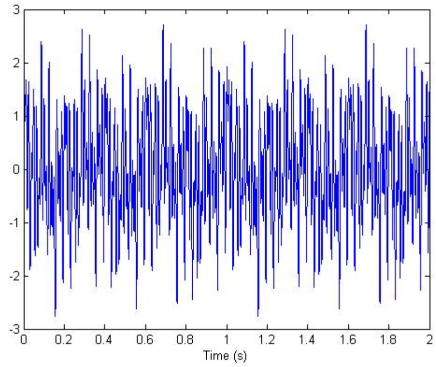
Figure 2.2: HHT Procedures

2.1.5 An Example of HHT

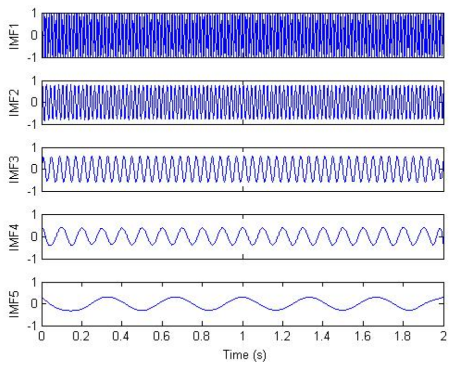
To provide an example of this method, we use the following signal as the input to the algorithm and examine the outputs of the algorithm:

$$x(t) = \cos(2\pi 80t) + 0.8\sin(2\pi 50t) + 0.6\sin(2\pi 25t) + 0.4\cos(2\pi 10t) + 0.3\cos(2\pi 3t) \tag{2.9}$$

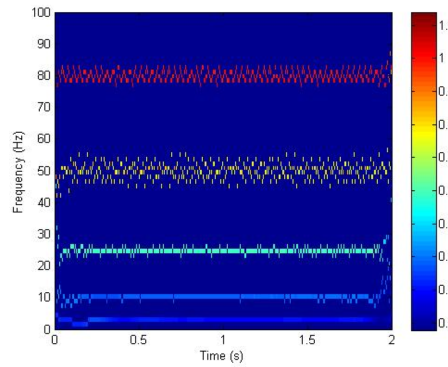
The signal $x(t)$ contains components with various amplitudes (1, 0.8, 0.6, 0.4, 0.3) and frequencies (80, 50, 25, 10, 3). The goal of this example is to test if the amplitude and frequency contents of the signal can be accurately extracted by the HHT method. As expected, the information was obtained with extreme accuracy. Figure 2.3 (a) is the original signal; figure 2.3 (b) shows the 5 extracted IMFs, each represents one of the expected five components; figure 2.3 (c) shows the Hilbert spectra of IMFs, which clearly shows the five frequencies along the vertical axis and the five amplitudes as individual colors; figure 2.3 (d) shows the marginal spectra and figure 2.3 (e) shows the energy density level of the signal, which is fairly constant because the signal is a sum of periodic signals.



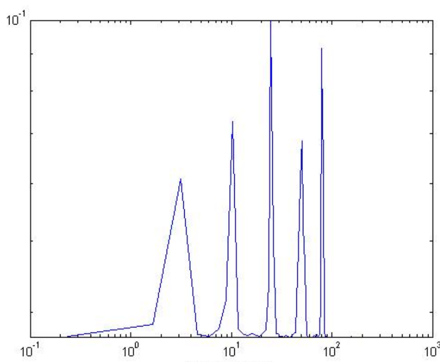
(a) Original Signal



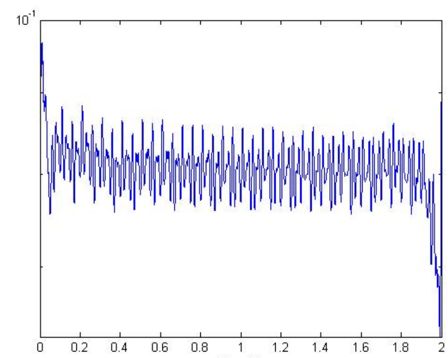
(b) IMFs



(c) Hilbert Spectrum



(d) Marginal Spectrum



(e) Energy Density Levels

Figure 2.3: Example of HHT Process

2.2 Hurst's Rescaled-Range(R/S) Method

Hurst parameter is a conventionally used measure of long-range dependence. There are many methods to estimate the self-similarity parameter H or the intensity of long-range dependence in a time series. In this paper, we use the Rescaled-Range(R/S) method [29].

For a time series, $X = \{X_i,\ i \geq 1\}$, with partial sum $Y(n) = \sum_{i=1}^{n} X_i$, and sample variance $S^2(n) = (1/n)\sum_{i=1}^{n} X_i^2 - (1/n)^2 Y^2(n)$, the R/S statistic, or the *rescaled adjusted range*, is given by:

$$\frac{R}{S}(n) = \frac{1}{S(n)}\left[\max_{0\leq t\leq n}\left(Y(t) - \frac{t}{n}Y(n)\right) - \min_{0\leq t\leq n}\left(Y(t) - \frac{t}{n}Y(n)\right)\right]. \tag{2.10}$$

For fractional Gaussian noise or fractional ARIMA, the expected value of the R/S statistic is:

$$E[\frac{R}{S}(n)] \backsim C_H n^H \tag{2.11}$$

as $n \to \infty$, where C_H is a positive, finite constant not dependent on n.

To determine H using the R/S statistic, proceed as follows:

1) For a time series of length N, subdivide the series into K blocks, each of size N/K.

2) For each lag n, compute $R(k_i,n)/S(k_i,n)$, starting at points $k_i = iN/K+1, i = 1,2,...,$ such that $k_i + n \leq N$. For values of n smaller than N/K, one gets K different estimates of $R(n)/S(n)$. For values of n approaching N, one gets fewer values, as few as 1 when $n \geq N - N/K$.

3) Choosing logarithmically spaced values of n, plot $\log[R(k_i,n)/S(k_i,n)]$ versus $\log n$ and get, for each n, several points on the plot. This plot is sometimes called the pox plot for the R/S statistic.

4) The parameter H can be estimated by fitting a line to the points in the pox plot.

Since any short-range dependence in the series typically results in a transient zone at the low end of the plot, set a cut-off point, and do not use the low end of the plot for the purpose of estimating H. Usually, the very high end of the plot is not used as well, because there are too few points on the plot at the high end to make reliable estimates. The values of n that lie between the lower and higher cut-off points are used to estimate H.

2.3 KDD Cup 1999 Testing Data

Since 1999, KDD'99 has been the most wildly used dataset for the evaluation of anomaly detection methods [30]. This dataset is prepared by Stolfo et al. [31] and is built based on the data captured in DARPA'98 IDS evaluation program [32]. DARPA'98 is about 4 gigabytes of compressed raw (binary) tcpdump data of 7 weeks of network traffic, which can be processed into about 5 million connection records, each with about 100 bytes. The two weeks of test data have around 2 million connection records. KDD training dataset consists of approximately 4,900,000 single connection vectors each of which contains 41 features and is labeled as either normal or an attack, with exactly one specific attack type. The simulated attacks fall in one of the following four categories:

1) **Denial of Service Attack (DoS):** is an attack in which the attacker makes some computing or memory resource too busy or too full to handle legitimate requests, or denies legitimate users access to a machine.

2) **User to Root Attack (U2R):** is a class of exploit in which the attacker starts out with access to a normal user account on the system (perhaps gained by sniffing passwords, a dictionary attack, or social engineering) and is able to exploit some vulnerability to gain root access to the system.

3) **Remote to Local Attack (R2L):** occurs when an attacker who has the ability to send packets to a machine over a network but who does not have an account on that machine exploits some vulnerability to gain local access as a user of that machine.

4) **Probing Attack:** is an attempt to gather information about a network of computers for the apparent purpose of circumventing its security controls.

It is important to note that the test data is not from the same probability distribution as the training data, and it includes specific attack types not in the training data which make the task more realistic. Some intrusion experts believe that most novel attacks are variants of known attacks and the signature of known attacks can be sufficient to catch novel variants. The datasets contain a total number of 24 training attack types, with an additional 14 types in the test data only. The name and detail description of the training attack types are listed in [33].

KDD99 features can be classified into three groups:

1) **Basic features:** this category encapsulates all the attributes that can be extracted from a TCP/IP connection. Most of these features leading to an implicit delay in detection.

2) **Traffic features:** this category includes features that are computed with respect to a window interval and is divided into two groups:

   a) **"same host" features:** examine only the connections in the past 2 seconds that have the same destination host as the current connection, and calculate statistics related to protocol behavior, service, etc.

   b) **"same service" features:** examine only the connections in the past 2 seconds that have the same service as the current connection.

   The two aforementioned types of "traffic" features are called time-based. However, there are several slow probing attacks that scan the hosts (or ports) using a much larger time interval than 2 seconds, for example, once every minute. As a result, these attacks do not produce intrusion patterns with a time window of 2 seconds. To solve this problem, the "same host" and "same service" features are re-calculated but based on the connection window of 100 connections rather than a time window of 2 seconds. These features are called connection-based traffic features.

3) **Content features:** unlike most of the DoS and Probing attacks, the R2L and U2R attacks do not have any intrusion frequent sequential patterns. This is because the DoS and Probing attacks involve many connections to some host(s) in a very short period of time; however the R2L and U2R attacks are embedded in the data portions of the packets, and normally involves only a single connection. To detect these kinds of attacks, we need some features to be able to look for suspicious behavior in the data portion, e.g., number of failed login attempts. These features are called content features.

A complete listing of the set of features defined for the connection records is given in the three tables below [34]:

Table 2.1: Basic features of individual TCP connections

Feature Name	*Description*	*Type*
duration	length (number of seconds) of the connection	continuous
protocol_type	type of the protocol, e.g. tcp, udp, etc.	discrete
service	network service on the destination, e.g., http, telnet, etc.	discrete
src_bytes	number of data bytes from source to destination	continuous
dst_bytes	number of data bytes from destination to source	continuous
flag	normal or error status of the connection	discrete
land	1 if connection is from/to the same host/port; 0 otherwise	discrete
wrong_fragment	number of “wrong” fragments	continuous
urgent	number of urgent packets	continuous

Table 2.2: Content features within a connection suggested by domain knowledge

Feature Name	*Description*	*Type*
hot	number of "hot" indicators	continuous
num_failed_logins	number of failed login attempts	continuous
logged_in	1 if successfully logged in; 0 otherwise	discrete
num_compromised	number of "compromised" conditions	continuous
root_shell	1 if root shell is obtained; 0 otherwise	discrete
su_attempted	1 if "su root" command attempted; 0 otherwise	discrete
num_root	number of "root" accesses	continuous
num_file_creations	number of file creation operations	continuous
num_shells	number of shell prompts	continuous
num_access_files	number of operations on access control files	continuous
num_outbound_cmds	number of outbound commands in an ftp session	continuous
is_hot_login	1 if the login belongs to the "hot" list; 0 otherwise	discrete
is_guest_login	1 if the login is a "guest" login; 0 otherwise	discrete

Table 2.3: Traffic features computed using a two-second time window

Feature Name	*Description*	*Type*
count	number of connections to the same host as the current connection in the past two seconds	continuous
Note: The following features refer to these same-host connections		
serror_rate	% of connections that have "SYN" errors	continuous
rerror_rate	% of connections that have "REJ" errors	continuous
same_srv_rate	% of connections to the same service	continuous
diff_srv_rate	% of connections to different services	continuous
srv_count	number of connections to the same service as the current connection in the past two seconds	continuous
Note: The following features refer to these same-service connections		
srv_serror_rate	% of connections that have "SYN" errors	continuous
srv_rerror_rate	% of connections that have "REJ" errors	continuous
srv_diff_host_rate	% of connections to different hosts	continuous

The KDD 99 intrusion detection benchmark consists of three components, which are detailed in Table 2.4. In the International Knowledge Discovery and Data Mining Tools Competition, only "10% KDD" dataset is employed for the purpose of training. This dataset contains 22 attack types and is a more concise version of the "Whole KDD" dataset.

It contains more examples of attacks than normal connections and the attack types are not represented equally. Because of their nature, Denial of Service attacks account for the majority of the dataset. On the other hand the “Corrected KDD” dataset provides a dataset with different statistical distributions than either “10% KDD” or “Whole KDD” and contains 14 additional attacks. The list of class labels and their corresponding categories for “10% KDD” are detailed in Table 2.5 [35].

Table 2.4: Basic characteristics of the KDD 99 intrusion detection datasets in terms of the number of samples

Dataset	DoS	Probe	U2R	R2L	Normal
“10% KDD”	391458	4107	52	1126	97277
“Corrected KDD”	229853	4166	70	16347	60593
“Whole KDD”	3883370	41102	52	1126	972780

Table 2.5: Class labels that appears in the “10% KDD” dataset

Attack	# Samples	Category
smurf.	280790	DoS
neptune.	107201	DoS
back.	2203	DoS
teardrop.	979	DoS
pod.	264	DoS
land.	21	DoS
normal.	97277	Normal
satan.	1589	Probe
ipsweep.	1247	Probe
portsweep.	1040	Probe
nmap.	231	Probe
warezclient.	1020	R2L
guess_passwd.	53	R2L
warezmaster.	20	R2L
imap.	12	R2L
ftp_write.	8	R2L
multihop.	7	R2L
phf.	4	R2L
spy	2	R2L
buffer_overflow.	30	U2R
rootkit.	10	U2R
loadmodule.	9	U2R
perl.	3	U2R

The kddcup.data_10_percent.gz dataset is used as the experiment data for this research. The data consist of 0.5 million sample points that represent about two weeks' worth of network traffic information. The data content used is the No. 23 field, which is the amount of data flow connected to the same host in the past 2s [36].

CHAPTER 3: NOVEL DETECTION METHODS

The HHT provides a new method of analyzing nonstationary and nonlinear time series data. It uses the EMD method to decompose a signal into Intrinsic Mode Functions, which represent the frequency and amplitude characteristics of that signal. It uses the Hilbert spectral analysis method to obtain instantaneous frequency information, which provides a method for examining the IMF's instantaneous frequencies as functions of time. The final presentation of the results is a magnitude-time-frequency distribution, designated as the Hilbert spectrum. Marginal spectrum is generated from the integral over time of the Hilbert spectrum, while the energy density level is generated from the integral over frequency of the Hilbert spectrum. The IMFs, the marginal spectrum, and the energy density level characterize a signal from three different perspectives.

The three novel detection methods for network traffic are proposed based on the above three signal characteristics. Hurst parameter of network traffic is calculated based on the first IMF, and is expanded by introducing a weighted self-similarity measure based on the concept of entropy. Pearson's distance is calculated based on the marginal spectrum to differentiate normal traffic from abnormal ones. Finally, the slopes of cross-correlations are calculated based on the energy density level to detect the rate of energy change between normal and abnormal internet traffic.

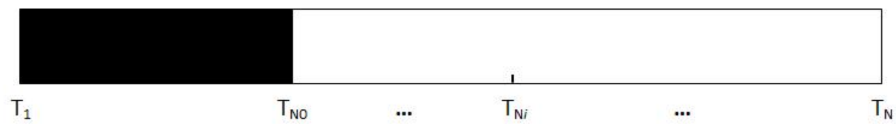
3.1 Weighted Self-similarity Based on the First IMF

In this section, the detection method using weighted self-similarity parameter is described.

3.1.1 Detection Algorithm

Apply EMD on the testing data to extract the first IMF signal. The weighted self-similarity parameter can be obtained as follows:

1) Set the Window Size:



We define T_N as our observation window size. Inside each observation window, calculate the initial Hurst parameter with a sub-window T_{N_0}, with the samples from $[1, N_0]$, where $N_0 < N$. Then calculate all the Hurst values from T_{N_0} to T_N. For example, the N_i^{th} Hurst parameter is calculated with samples from $[1, N_i]$, where $N_i = N_0 + 1,\ N_0 + 2,\ N_0 + 3,\ \ldots,\ N$.

2) Calculate the probability P and average of Hurst value H_{avg}, repeat for M iterations:

$N_H =$ total number of Hurst values per window

$H_{min} =$ minimum of Hurst values in the window

$H_{max} =$ maximum of Hurst values in the window

Divide $[H_{min}\ H_{max}]$ into k bins:

N_{ji} = number of Hurst values in bin i at the j^{th} iteration

H_{ji} = Hurst value in bin i at the j^{th} iteration

$(i = 1,\ 2,\ \ldots,\ k,\ \ j = 1,\ 2,\ \ldots,\ M)$

For each bin i at the j^{th} iteration, the probability of Hurst is calculated as follows:

$$P_{ji} = \frac{N_{ji}}{N_H} \tag{3.1}$$

$$P = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1k} \\ P_{21} & P_{22} & \cdots & P_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ P_{M1} & P_{M2} & \cdots & P_{Mk} \end{bmatrix} \tag{3.2}$$

The average of Hurst values in bin i at the j^{th} iteration is calculated as follows:

$$H_{ji} = \frac{\sum_{n=1}^{N_{ji}} H_{ji}(n)}{N_{ji}} \tag{3.3}$$

where $i = 1,\ 2,\ ...,\ k,\ \ j = 1,\ 2,\ ...,\ M$. The average Hurst values in each bin for each iteration can be organized in the following matrix:

$$H_{avg} = \begin{bmatrix} H_{11} & H_{12} & \cdots & H_{1k} \\ H_{21} & H_{22} & \cdots & H_{2k} \\ \vdots & \vdots & \ddots & \vdots \\ H_{M1} & H_{M2} & \cdots & H_{Mk} \end{bmatrix} \tag{3.4}$$

When establishing the reference profile, H_{avg} is a $10 \times k$ matrix, and it is a $1 \times k$ vector when performing detection.

3) Calculate the weighted self-similarity parameter for j^{th} iteration:

$$H_W(j) = -\sum_{i=1}^{k} H_{ji} \log_2 P_{ji} \tag{3.5}$$

where k is the number of bins, $j = 1,\ 2,\ ...,\ M$.

When establishing the reference profile, $M = 10$, and $H_W(j)$ is a 1×1 vector. The average value of the vector entries help us establish the thresholds. When performing detection, $M = 1$, $H_W(j)$ is a single value, H_W, which we define as the Weighted Self-similarity parameter.

4) Follow the above steps to develop a reference profile and two thresholds, H_{Wth1} and H_{Wth2} respectively. For real-time detection, the weighted self-similarity H_W is compared with H_{Wth1} to decide whether attacks exist or not; if we decide there are attacks in the traffic, H_W needs to be compared with H_{Wth2} to decide whether attacks are over or not. To provide a visual comparison, the probability vs. H_{avg} and reference can be plotted against each other to show the changes in distribution. More details are provided in the next section.

3.1.2 Attack-Free Reference

Perform the EMD method on kddcup.data_10_percent.gz dataset. The first 11000s (5500 samples) data were used to build 10 attack free reference windows, each window length is 2000s (1000 samples). The weighted self-similarity parameter of each window was calculated. By averaging P and Havg of the 10 reference windows, the reference profile was established.

3.1.3 Detection Criteria

In the experiments, we set $H_{Wth1} = 23$, $H_{Wth2} = 35$ as the two thresholds, the detection criteria are shown as follows:

$$\begin{cases} H_W \le H_{Wth1} & \text{Traffic Normal} \\ H_W > H_{Wth1} & \text{Attacks} \\ H_W > H_{Wth2} & \text{Attacks Stopped} \end{cases}$$

Move the observation window along this dataset, we can predict attacks by comparing the weighted self-similarity value to our threshold. If H_W is smaller than H_{Wth1}, the traffic is normal; if H_W is greater than H_{Wth1}, we decide there are attacks in the traffic; if H_W is smaller than H_{Wth2}, we can predict that the attacks are still there, keep tracking on the data until the attacks are over.

3.2 Pearson's Distance Based on Marginal Spectrum

In this section we propose the second method by calculating Pearson's distance based on Hilbert Marginal Spectrum.

The Pearson's distance is defined as follows: given two random variables X and Y, $var(X)$ is the variance of X, $var(Y)$ is the variance of Y, $cov(X,Y)$ is the covariance of X and Y, then the Pearson's correlation coefficient is defined as:

$$r = \frac{cov(X,Y)}{\sqrt{var(X)\ var(Y)}} \tag{3.6}$$

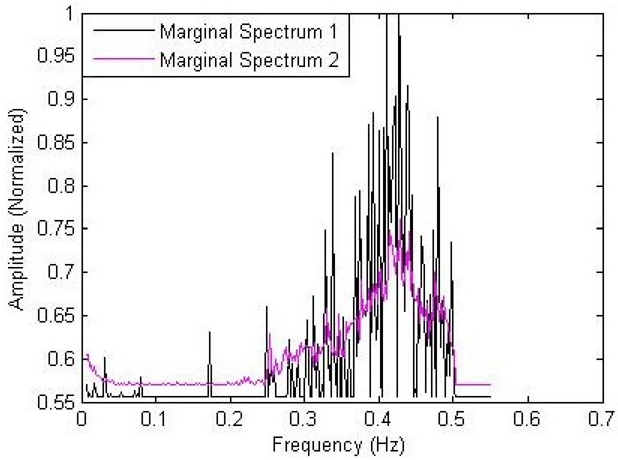
and the Pearson's distance is defined as:

$$d_{X,Y} = 1 - |r| \tag{3.7}$$

3.2.1 Detection Algorithm

Pearson's distance is calculated based on the marginal spectrum to differentiate normal traffic from abnormal ones.

Suppose we obtained the first IMF through the EMD process, the two Hilbert Marginal Spectra are shown in Figure 3.1 as follows:



	Marginal Spectrum 1	Marginal Spectrum 2
Var	0.0080	0.0021
Cov	0.0030	
r	0.7275	
d	0.2725	

Figure 3.1: Marginal Spectrum & Pearson's Distance

We can measure the linear relationship between these two Marginal Spectra by calculating the Pearson's Distance. Pearson's distance is always between 0 and 1, where 0 (or $|r| = 1$) means two spectra are identical and 1 (or $r = 0$) means they are completely uncorrelated [37]. With a reference attack-free marginal spectrum, if the marginal spectrum of data under test is highly correlated with the reference, we decide the traffic is normal. Otherwise, it is expected that attacks may have occurred in the network traffic.

3.2.2 Attack-Free Reference

Perform the EMD on the kddcup.data_10_percent.gz dataset. The first 12000s (6000 samples) data were used to build 30 attack free reference windows, each window length is 400s (200 samples). The Pearson's distance was calculated based on marginal spectrum for each window. By averaging the distance of the 30 reference windows, the reference profile was established.

3.2.3 Detection Criteria

In the experiments, we set $d_{th} = 0.5000$ as our threshold, the detection criteria are shown as follows:

$$\begin{cases} d \leq d_{th} & \text{Traffic Normal} \\ d > d_{th} & \text{Attacks} \end{cases}$$

3.3 Rate Change of Energy Density Level

Slopes of cross-correlations are calculated based on the energy density level to detect the rate of energy change between normal and abnormal internet traffic.

As the autocorrelation is symmetrical (shown in Figure 3.2), we only focus on the first half of the autocorrelation to detect the attacks. Divide the first half into two parts, then calculate the two slopes to detect the slope change in energy.

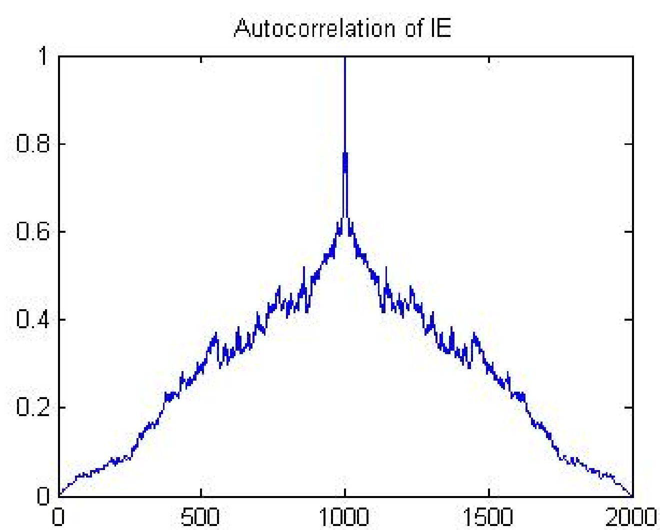


Figure 3.2: Autocorrelation of Energy Density Level

3.3.1 Detection Algorithm

Suppose we obtained the energy density through the HHT process: $IE(t) = \int_{\omega} H^2(\omega, t) d\omega$. The autocorrelation of the energy density level is shown in Figure 3.3, and the detection algorithm is as follows:

1) Set window size = 1000 sample points.

2) Use regression to calculate the slope m_1 of the first 500 sample points and the slope m_2 of the second 500 sample points.

3) Calculate the rate of energy change $\Delta m = m_2 - m_1$, we can detect the abnormal activities from the normal ones - a small Δm means normal traffic while a large Δm indicates attacks in the traffic.

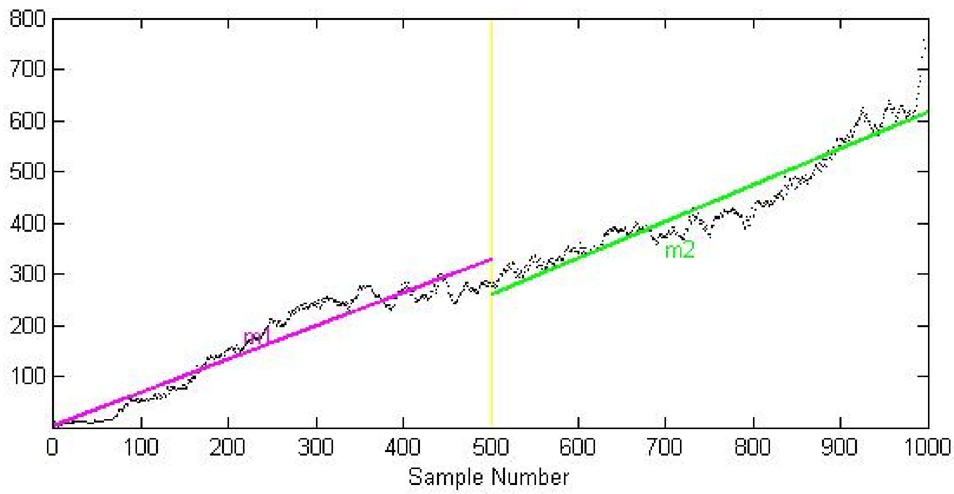


Figure 3.3: Autocorrelation of Energy Density Level (First Half)

3.3.2 Detection Criteria

In the experiments, we set $m_{th} = 0.5000$ as our threshold, the detection criteria are shown as follows:

$$\begin{cases} \Delta\, m \le m_{th} & \text{Traffic Normal} \\ \Delta\, m > m_{th} & \text{Attacks} \end{cases}$$

CHAPTER 4: RESULTS AND ANALYSIS

4.1 Pre-treat the Testing Data

There are 4 types of attacks in the kddcup.data_10_percent.gz dataset: DoS, U2R, R2L and probing. As we only focus on DoS attacks, we pre-treat the testing data as follows:

1) Read the testing data, mark all the DoS attacks (Smurf, Neptune, Back, Teardrop, Pod and Land) as '0' and the rest as '1': normal.

2) In each observation window, if there is a '0', we will mark the window as '0': DoS attacks; if there are all '1's in the whole observation window, we will mark the window as '1': normal.

4.2 Testing Results

4.2.1 Weighted Self-similarity Based on the First IMF

Ran test on kddcup.data_10_percent.gz dataset with Denial of Service (DoS) attacks. Set the window size at 1000 data points (which is 2000 seconds in time). Since the total length of kddcup.data_10_percent.gz dataset is 494021 data points, there are 987 windows for testing. Tested 987 windows in total, and 616 windows were correctly detected (Note: when doing this testing, we only concerned about whether there were attacks in the observation windows, and this detection rate was calculated by using H_{Wth1} only).

The detection rate for DoS attacks is: $\frac{616}{987} = 62.41\%$.

This detection rate surprised us as it was lower than we expected. After checking the results, we noticed that the detection of almost all "Neptune" attacks failed, which means the weighted self-similarity method did not work well on "Neptune" attacks. Maybe this method can not capture the characteristics of the "Neptune" attacks. So we took away this type of DoS attack from the testing data, and ran the same test, the detection rate without "Neptune" attacks is: $\frac{776}{987} = 78.62\%$.

Figure 4.1 shows a case where no attacks occurred in the network traffic. Figure 4.1(a) is the original data. Figure 4.1(b) is the first IMF extracted from the original data. Figure 4.1(c) include reference H_{avg} vs. $Probability$ (attack free, in red) and the currently calculated H_{avg} vs. $Probability$ (attack free data under test, in black) plots. As can be observed from figure 4.1(c), the calculated attack free distribution overlaps with the reference distribution, indicating that the traffic under test does not have attacks. In actual test, H_W of the data under test is 18.9220. As $18.9220 < H_{Wth1}$, we conclude that the traffic is normal.

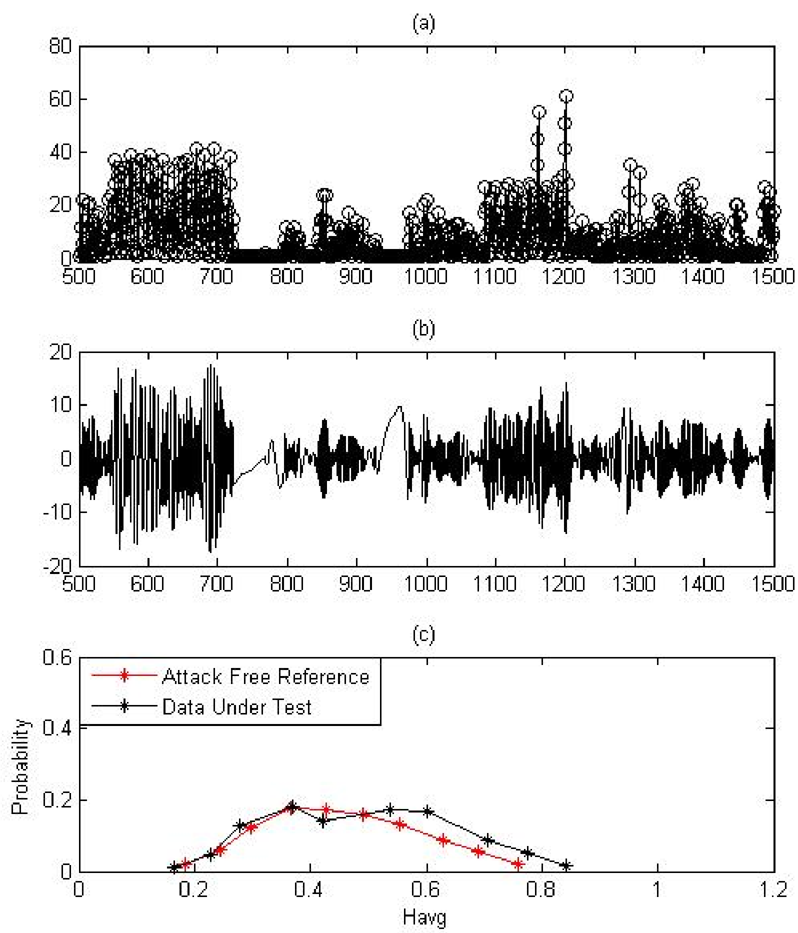


Figure 4.1: Weighted Self-similarity Example 1: Normal Data

(a) Data Under Test (b) First IMF (c) H_{avg} vs. Probability

Figure 4.2 presents a case where attacks started around data point 7800. As can be observed from figure 4.2(c), the H_{avg} vs. $Probability$ distribution shifted to the right compared with the reference distribution, indicating the start of an attack in network traffic. Indeed, H_W of data with attacks is $23.8944 > H_{Wth1}$, we conclude that attacks just began in the network traffic.

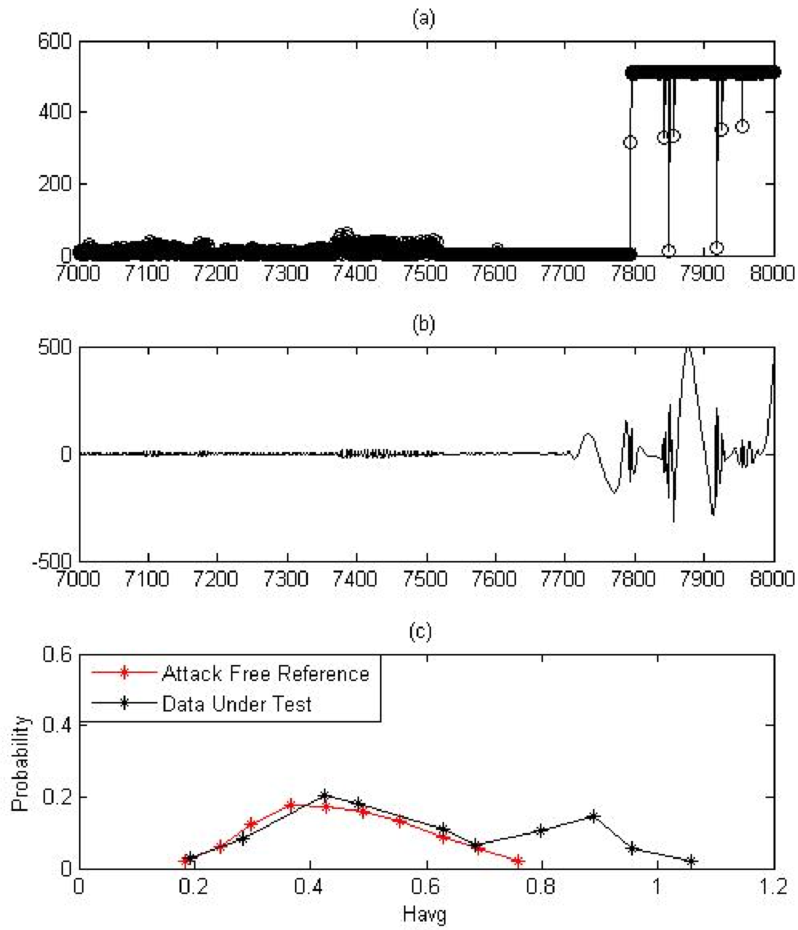


Figure 4.2: Weighted Self-similarity Example 1: Data With Attacks

(a) Data Under Test (b) First IMF (c) H_{avg} vs. Probability

Figure 4.3 shows a case where the data under test includes attacks only. As can be observed from figure 4.3(c), the H_{avg} vs. $Probability$ distribution significantly shifted away from the reference. Again, H_W of all attacks data is 25.9630 $> H_{Wth1}$, we conclude that there are still attacks in the network traffic.

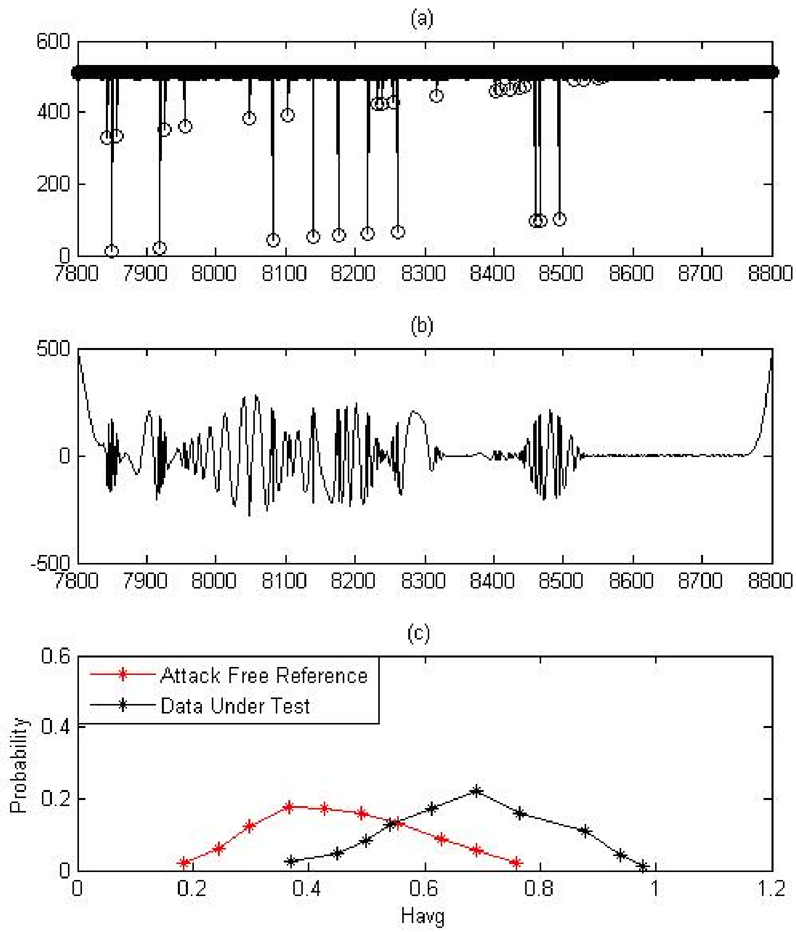


Figure 4.3: Weighted Self-similarity Example 1: All Attacks Data

(a) Data Under Test (b) First IMF (c) H_{avg} vs. Probability

Figure 4.4 shows a case when network traffic attacks stopped. As can be seen from figure 4.4(c), the H_{avg} vs. $Probability$ distribution of data under test is significantly narrower and completely shifted away from the attack free reference. This is an indication that the attacks have stopped. The H_W of the data under test is 54.0850. As 54.0850 $> H_{Wth2}$, we conclude that the attacks are over.

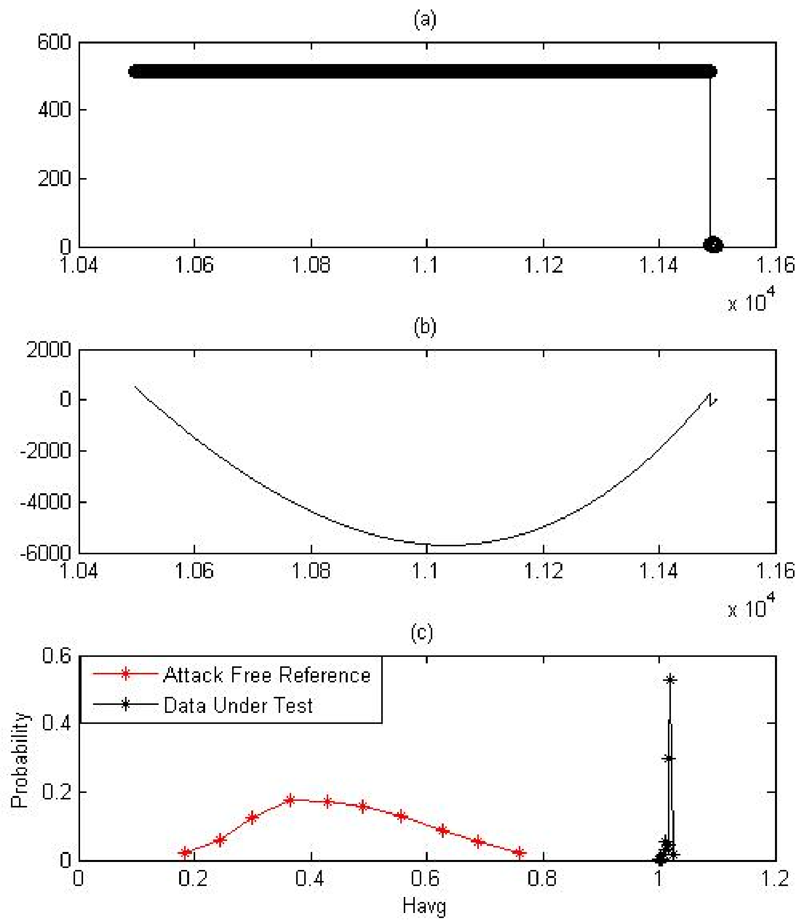
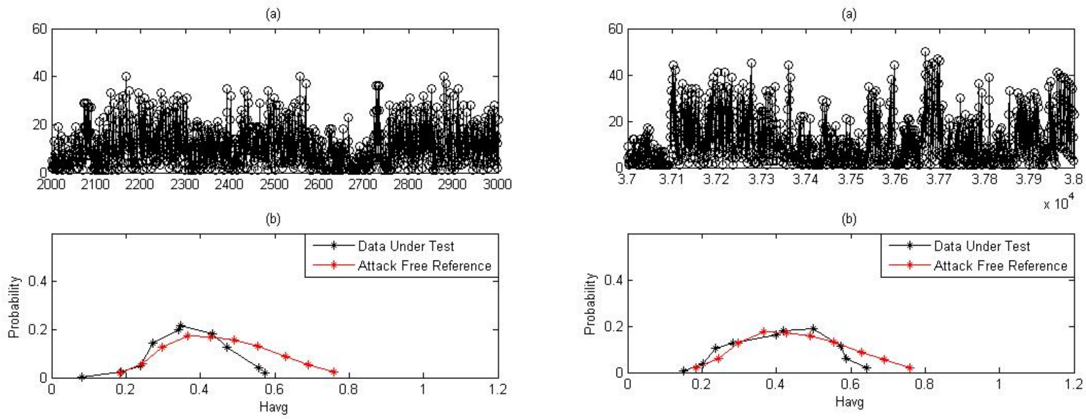


Figure 4.4: Weighted Self-similarity Example 1: Attacks Stopped Data

(a) Data Under Test (b) First IMF (c) H_{avg} vs. Probability

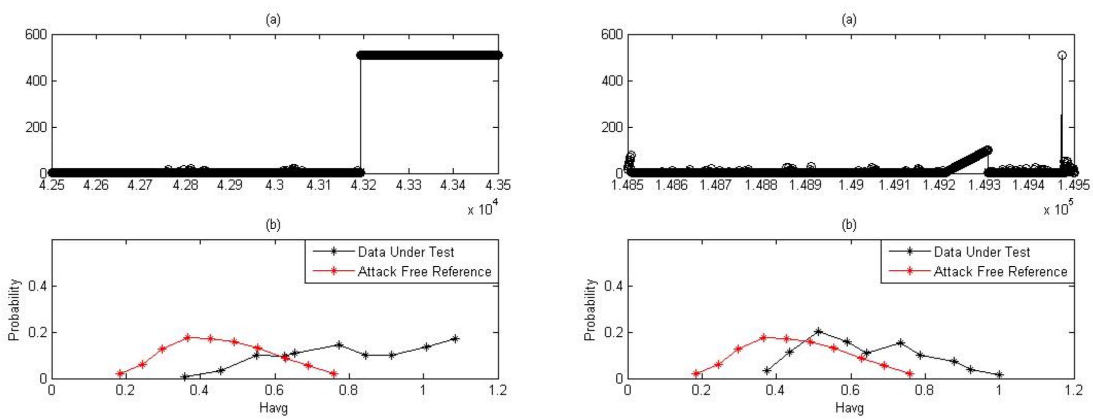
More testing results are shown as follows: Figure 4.5 shows the normal data of sample points at [2001, 3000] and [37001, 38000]; Figure 4.6 shows data with attacks of sample points at [42501, 43500] and [148501, 149500].



$H_W = 13.5088$ $\qquad$ $H_W = 14.8722$

Figure 4.5: Weighted Self-similarity Example 2: Normal Data

(a) Data Under Test (b) H_{avg} vs. Probability

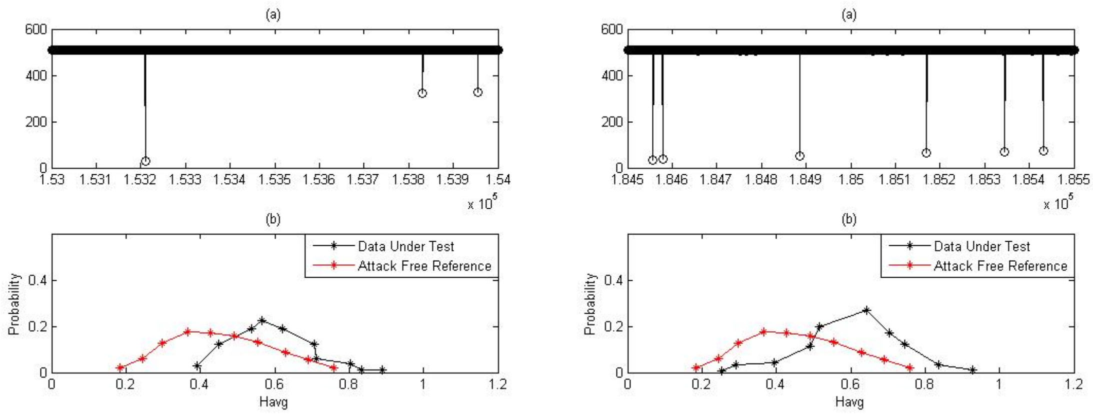


$H_W = 24.3820$ $\qquad$ $H_W = 26.1997$

Figure 4.6: Weighted Self-similarity Example 2: Data With Attacks

(a) Data Under Test (b) H_{avg} vs. Probability

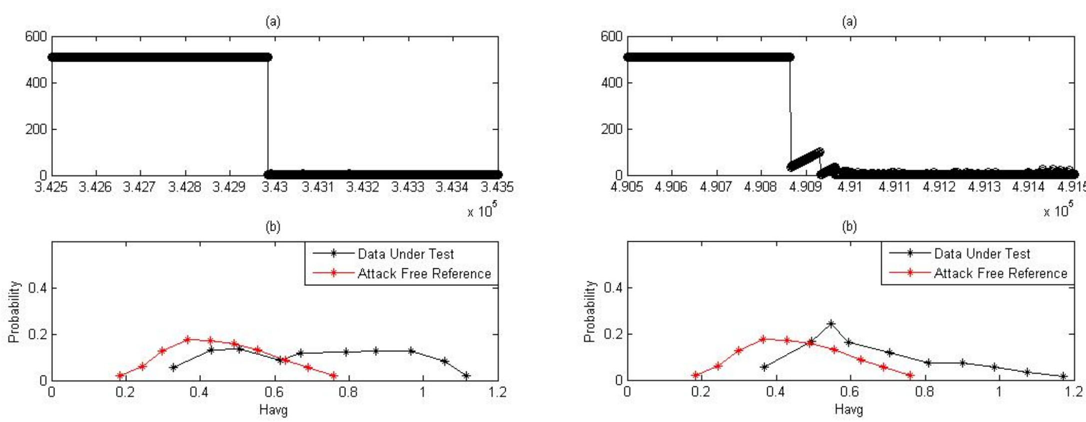
Figure 4.7 shows all attacks data of sample points at [153001, 154000] and [184501, 185500]; Figure 4.8 shows attacks stopped data of sample points at [342501, 343500] and [490501, 491500] (Note: as automated test did not change the window size, Figure 4.8 is different from Figure 4.4).



$H_W = 27.3815$ $\qquad$ $H_W = 23.2611$

Figure 4.7: Weighted Self-similarity Example 2: All Attacks Data

(a) Data Under Test (b) H_{avg} vs. Probability



$H_W = 26.3518$ $\qquad$ $H_W = 30.3625$

Figure 4.8: Weighted Self-similarity Example 2: Attacks Stopped Data

(a) Data Under Test (b) H_{avg} vs. Probability

Complete testing results can be found in Appendix A.

4.2.2 Pearson's Distance Based on Marginal Spectrum

Ran test on kddcup.data_10_percent.gz dataset with Denial of Service (DoS) attacks. Set the window size at 200 data points (which is 400 seconds in time), as the total length of kddcup.data_10_percent.gz dataset is 494021 data points, so there will be 2469 windows for testing. Tested 2469 windows in total, and 2216 windows were correctly detected.

The detection rate for DoS attacks is: $\frac{2216}{2469} = 89.75\%$

Figure 4.9 shows a case where no attacks occurred in the network traffic. As can be observed from the figure, the marginal spectrum of normal data almost overlaps with the attack free reference. The Pearson's distance between "Data Under Test" and "Attack Free Reference" is 0.2804, and $0.2804 < d_{th}$, the traffic is normal (where d_{th} is 0.5000).

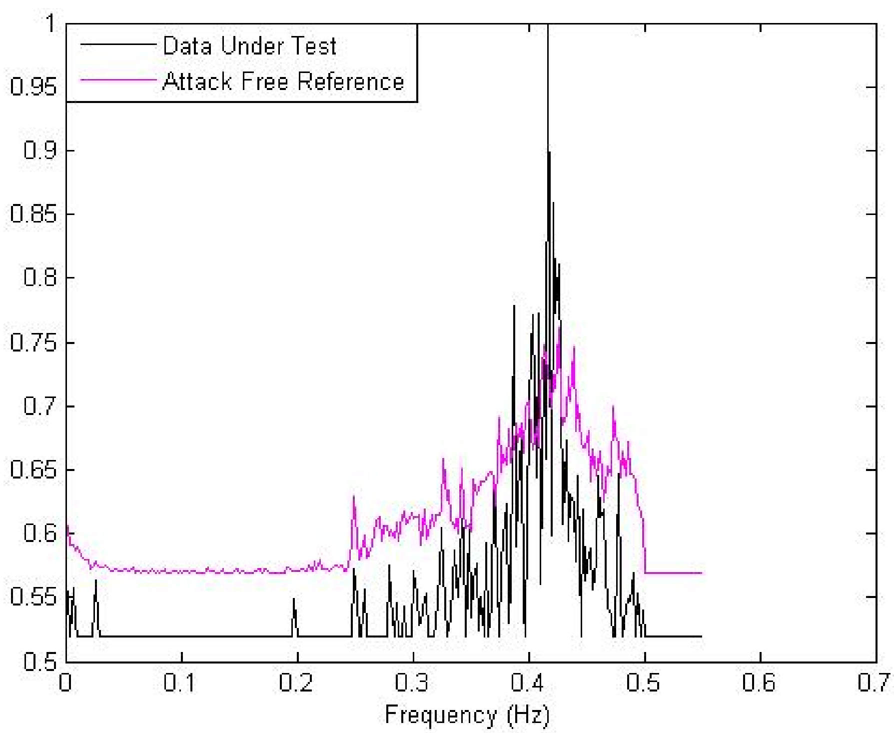


Figure 4.9: Marginal Spectrum Example 1: Normal Data

Figure 4.10 shows a case where attacks occurred in the network traffic. As can be observed from the figure, the marginal spectrum of data with attacks has a peak between 0.2 and 0.3, and the shape is totally different with the attack free reference. The Pearson's distance between "Data Under Test" and "Attack Free Reference" is 0.9529, and 0.9529 $> d_{th}$, we conclude that there are attacks in the traffic (where d_{th} is 0.5000).

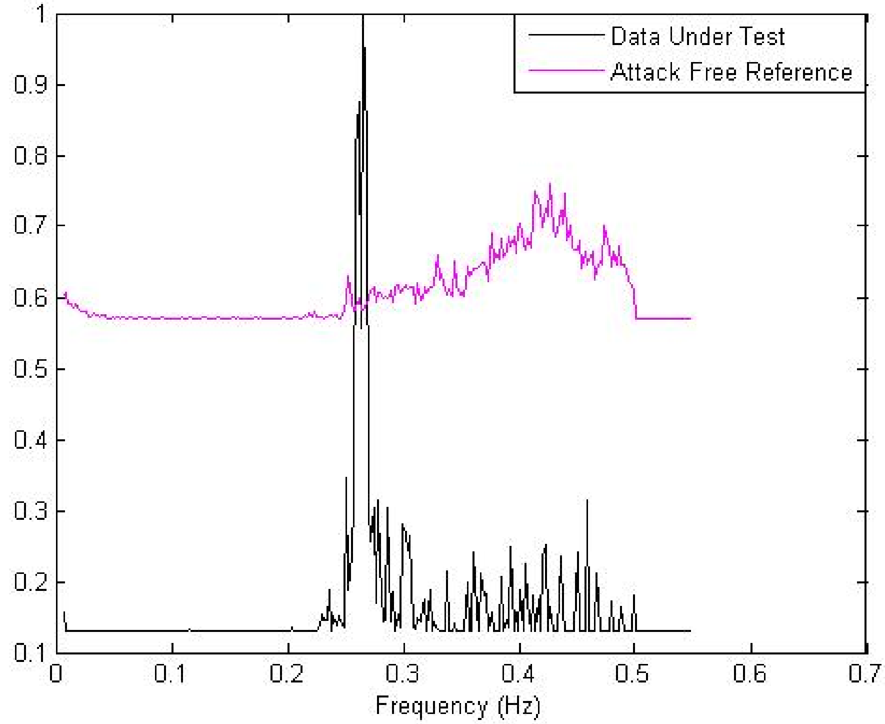
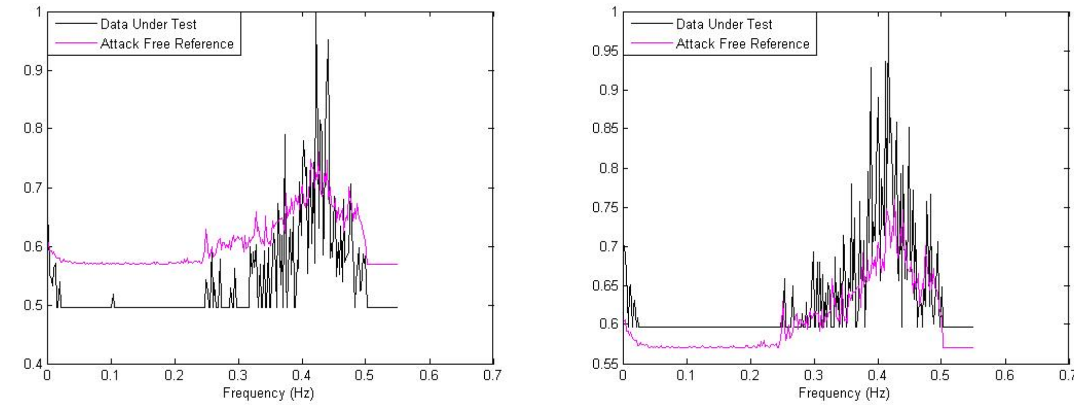


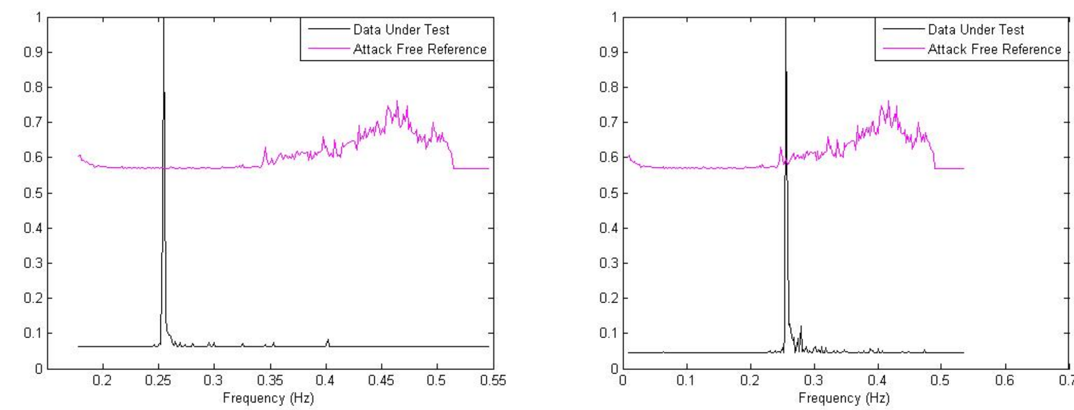
Figure 4.10: Marginal Spectrum Example 1: Data With Attacks

More testing results are shown as follows:



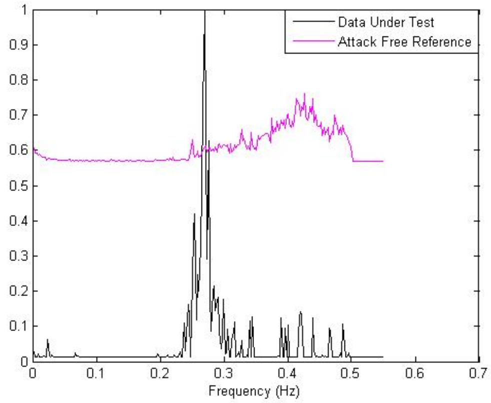
Pearson's $d = 0.2510$ Pearson's $d = 0.2455$

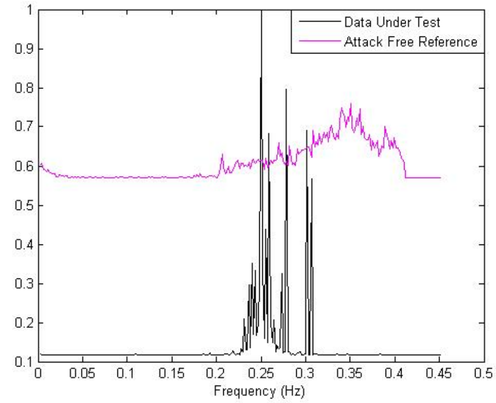
Figure 4.11: Marginal Spectrum Example 2: Normal Data



Pearson's $d = 0.9219$ Pearson's $d = 0.9814$

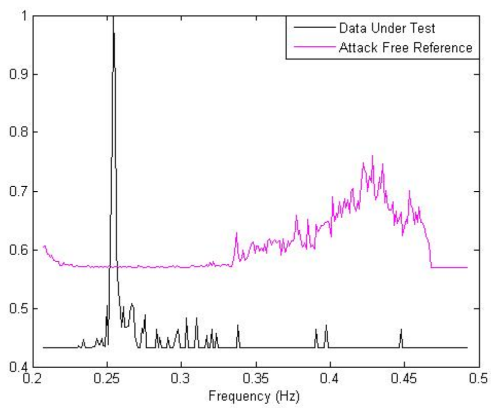
Figure 4.12: Marginal Spectrum Example 2: Data With Attacks

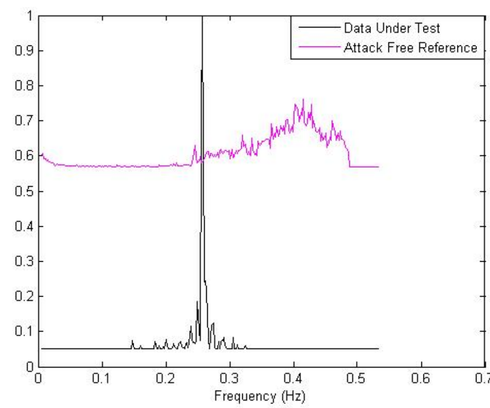




Pearson's $d = 0.9604$ Pearson's $d = 0.9474$

Figure 4.13: Marginal Spectrum Example 2: All Attacks Data





Pearson's $d = 0.8431$ Pearson's $d = 0.9361$

Figure 4.14: Marginal Spectrum Example 2: Attacks Stopped Data

Complete testing results can be found in Appendix B.

4.2.3 Rate Change of Energy Density Level

Ran test on kddcup.data_10_percent.gz dataset with Denial of Service (DoS) attacks. Set the window size at 1000 data points (which is 2000 seconds in time), as the total length of kddcup.data_10_percent.gz dataset is 494021 data points, so there will be 987 windows for testing. Tested 987 windows in total, and 747 windows were correctly detected.

The detection rate for DoS attacks is: $\frac{747}{987} = 75.68\%$

Figure 4.15 shows a case where no attacks occurred in the network traffic. As can be observed from the figure, the slopes of m_1 and m_2 are not much different, and they follow the same trend. The rate of energy change $\Delta m = m_1 - m_2 = 0.6125 - 0.5859 = 0.0266$, and $0.0266 < m_{th}(0.5000)$, the traffic is normal.

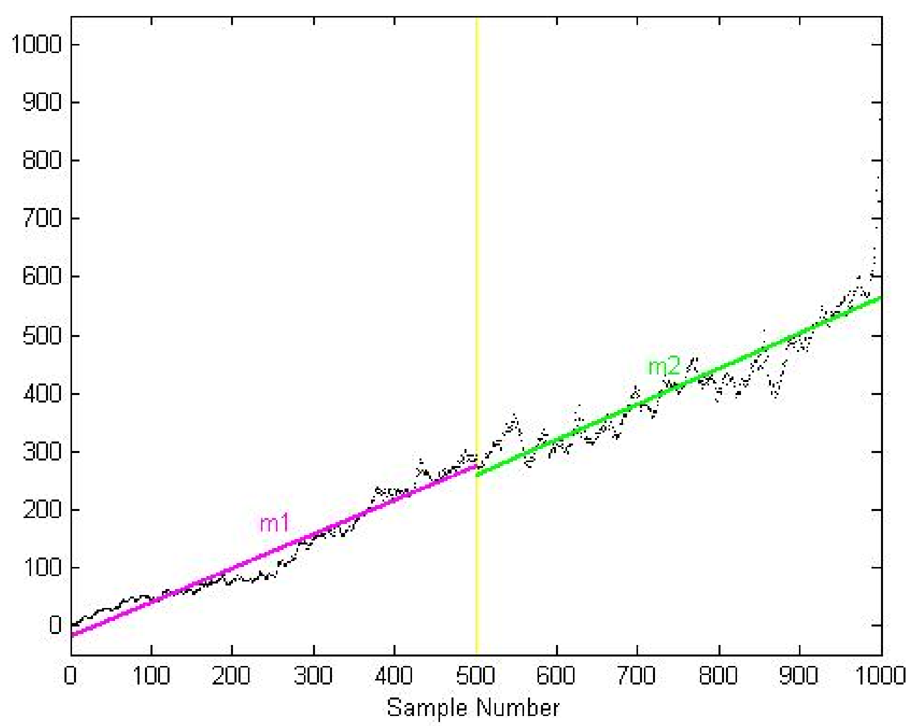


Figure 4.15: Autocorrelation of Energy Density Level Example 1: Normal Data

Figure 4.16 shows a case where attacks occurred in the network traffic. As can be observed from the figure, the slopes have a significant change between m_2 and m_1, and they do not follow the same trend any more. The rate of energy change $\Delta m = m_1 - m_2 = 2.1155 - 0.0006 = 2.1149$, and $2.1149 > m_{th}(0.5000)$, we conclude that there are attacks in the traffic.

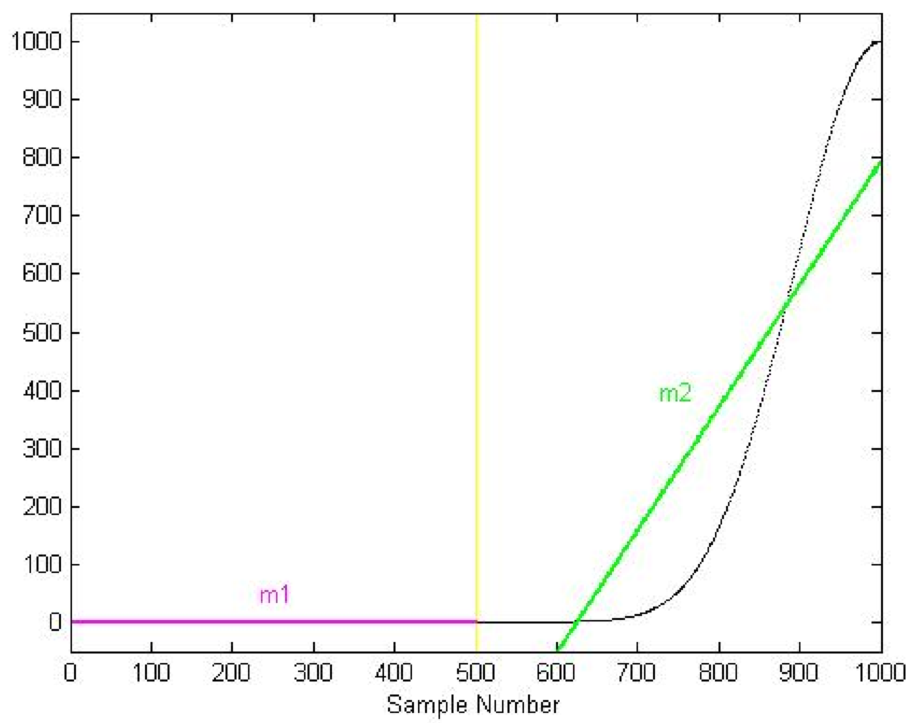
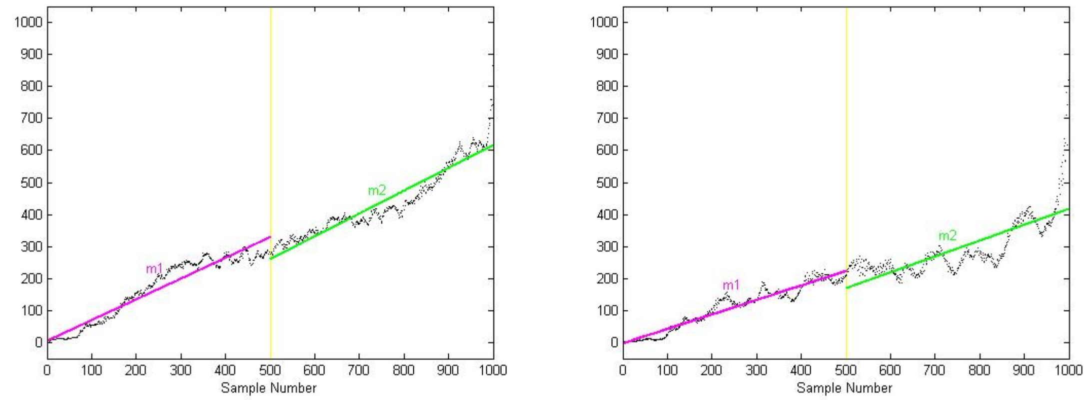


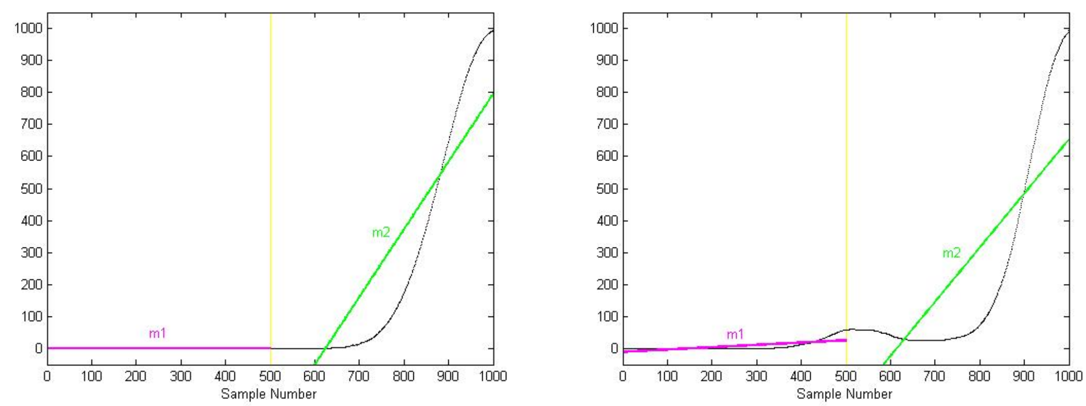
Figure 4.16: Autocorrelation of Energy Density Level Example 1: Data With Attacks

More testing results are shown as follows:



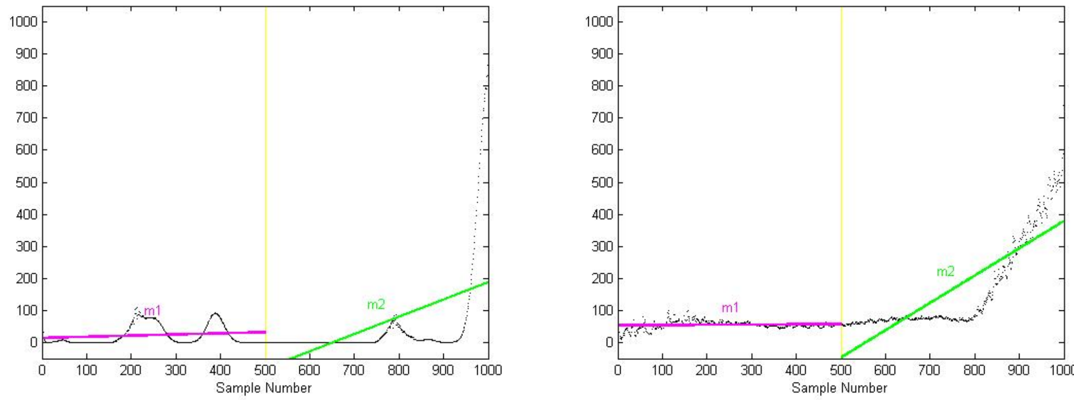
$\Delta m = m_2 - m_1 = 0.0643$ $\qquad$ $\Delta m = m_2 - m_1 = 0.0435$

Figure 4.17: Autocorrelation of Energy Density Level Example 2: Normal Data



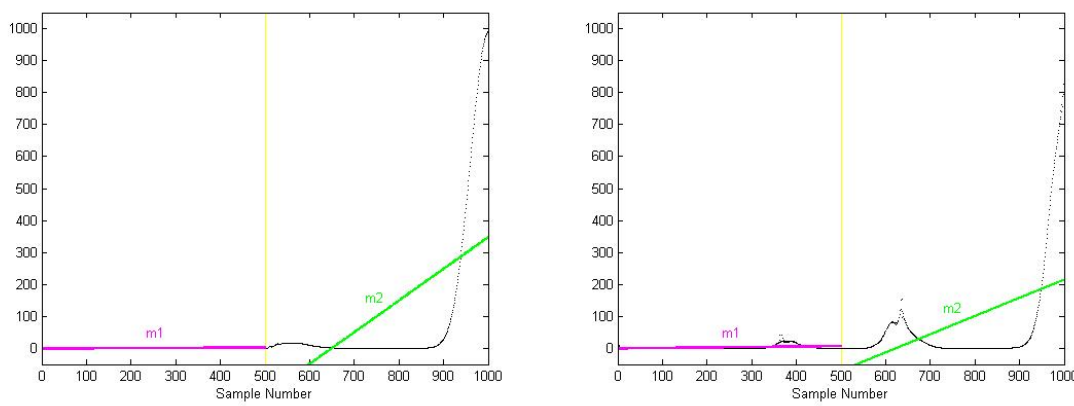
$\Delta m = m_2 - m_1 = 2.1162$ $\qquad$ $\Delta m = m_2 - m_1 = 1.6202$

Figure 4.18: Autocorrelation of Energy Density Level Example 2: Data With Attacks



$\Delta m = m_2 - m_1 = 0.5037$ $\Delta m = m_2 - m_1 = 0.8439$

Figure 4.19: Autocorrelation of Energy Density Level Example 2: All Attacks Data



$\Delta m = m_2 - m_1 = 0.9836$ $\Delta m = m_2 - m_1 = 0.5547$

Figure 4.20: Autocorrelation of Energy Density Level Example 2: Attacks Stopped Data

Complete testing results can be found in Appendix C.

CHAPTER 5: CONCLUSION AND FUTURE WORK

This thesis proposed three novel methods for network traffic anomaly detection based on three signal characteristics: the first IMF, marginal spectrum and energy density level. The weighted self-similarity parameter is calculated based on the first IMF and is introduced with the concept of entropy. Pearson's distance is calculated based on the marginal spectrum to differentiate normal traffic from abnormal ones. And the rate change of energy density level is calculated based on the difference of slopes of autocorrelation.

Experimental test results on kddcup.data_10_percent.gz dataset with Denial of Service attacks show improved detection rates of network traffic anomaly – the weighted similarity parameter provides a 62.4% detection rate (without the "Neptune" in the DoS attacks, the detection rate was 78.62%): 616 out of 987 windows were correctly detected; the energy density based detection provides a 75.7% detection rate: 747 out of 987 windows were correctly detected; and the Pearson's distance yields an 89.8% detection rate: 2216 out of 2469 windows were correctly detected.

Future work includes: (1) Refine each method to future improve the detection rate. (2) Adjust the window size of each method and utilize a combination of the three parameters, to achieve attack-specific, accurate, and timely detection. (3) Collect real-time data from a network to verify the robustness of the proposed detection methods.

BIBLIOGRAPHY

[1] S. Papavassiliou, M. Pace, and L. Ho, "Implementing enhanced network maintenance for transaction access services: Tools and applications," in *IEEE International Conference on Communications*, vol. 1, pp. 211- 215, 2000.

[2] D. H. Kang, B. K. Kim, and J. T. Oh, "Protocol anomaly and pattern matching based intrusion detection system," in *WSEAS Transactions on Communication*, vol.4, no. 10, pp. 994-1101, 2005.

[3] M. Thottan and J. Chuanyi, "Anomaly detection in IP networks," in *IEEE Trans. on Signal Processing*, vol. 51, no. 8, pp. 2191-2204, 2003.

[4] L. Feinstein, and et al., "Statistical approaches to DDoS attack detection and response," in *Proc., DARPA information survivability conference and exposition proceedings*, vol. 1, pp. 303-314, 2003.

[5] M. Li, "An approach to reliably identifying signs of DDoS flood attacks based on LRD traffic pattern recognition," in *Computers & Security*, vol. 23, pp. 549-558, 2004.

[6] M. H. Li, M. Li, and X. Y. Jiang, "DDoS attacks detection model and its application," in *WSEAS Transactions on Computers*, Issue 8, vol. 7, pp. 1159-168, 2008.

[7] M. Li, "Change trend of averaged Hurst parameter of traffic under DDoS flood attacks," in *Computers & Security*, vol. 25, no. 3, pp. 213-220, 2006.

[8] S. S. Kim, A. L. N. Reddy, and M. Vannucci, "Detecting traffic anomalies through aggregate analysis of packet header data," in *International IFIT-TC6 Networking Conference*, Greece, vol. 3042, pp. 1047-1059, 2004.

[9] P. Abrey, R. Baraniuk, P. Flaudrin, R. Riedi, and D. Veitch, “Multiscale nature of network traffic,” in *IEEE Signal Processing Magazine*, pp. 28-46, 2002.

[10] X. Wang, L. Pang Q. Pei and X. Li, “A scheme for fast network traffic anomaly detection,” in *Computer Application and System Modeling*, Xi’an, China, pp. V1-592-V1-596, 2010.

[11] H. Jiang, L. pang, “Fast Network Traffic Anomaly Detection Based on Iteration,” *Computational Intelligence and Security(CIS), 2011 Seventh International Conference*, vol., no., pp.1006-1010, Dec 2011.

[12] Limthong, K.; Watanapongse, P.; Kensuke, F. “A wavelet-based anomaly detection for outbound network traffic,” in *Information and Telecommunication Technologies (APSITT)*, pp.1-6, 15-18 June 2010.

[13] J. D. Brutlag, “Aberrant behavior detection in time series for network monitoring,” in *LISA ’00: Proceedings of the 14th USENIX conference on System administration*, Berkeley, CA, USA: USENIX Association, pp. 139-146, 2000.

[14] C.-M. Cheng, H. Kung, and K.-S. Tan, “Use of spectral analysis in defense against DoS attacks,” in *Global Telecommunications Conference, 2002. GLOBECOM ’02. IEEE*, vol. 3, pp. 2143-2148 vol.3, Nov. 2002.

[15] Y. Chen and K. Hwang, “Spectral analysis of tcp flows for defense against reduction-of-quality attacks,” in *Communications, 2007. ICC ’07. IEEE International Conference*, pp. 1203-1210, June 2007.

[16] Y. Gu, A. McCallum, and D. Towsley, “Detecting anomalies in network traffic using maximum entropy estimation,” in *IMC ’05: Proceedings of the 5th ACM SIGCOMM conference on Internet Measurement*, Berkeley, CA, USA: USENIX Association, pp. 32-32, 2005.

[17] A. Wagner and B. Plattner, "Entropy based worm and anomaly detection in fast IP networks," in *Enabling Technologies: Infrastructure for Collaborative Enterprise, 2005. 14th IEEE International Workshops*, pp. 172-177, June 2005.

[18] A. Lakhina, M. Crovella, and C. Diot, "Diagnosing network-wide traffic anomalies," in *SIGCOMM '04: Proceedings of the 2004 conference on Applications, technologies, architectures, and protocols for computer communications*, New York, NY, USA: ACM, pp. 219-230, 2004.

[19] B. I. P. Rubinstein, B. Nelson, L. Huang, A. D. Joseph, S.-h. Lau, N. Taft and D. Tygar, "Compromising pca-based anomaly detectors for network-wide traffic," EECS Department, University of California, Berkeley, Tech. Rep. UCB/EECS-2008-73, May 2008.

[20] H. Ringberg, A. Soule, J. Rexford, and C. Diot, "Sensitivity of pca for traffic anomaly detection," in *SIGMETRICS Perform. Eval. Rev.*, vol. 35, no. 1, pp. 109-120, 2007.

[21] V. Alarcon-Aquino and A. Barria, "Anomaly detection in communication networks using wavelets," in *IEEE Proc-Commun*, vol. 148, no. 6, pp. 355-362, 2001.

[22] A. Ramanathan, "WADeS: A tool for distributed denial of service attack detection," in *TAMU-ECE-2002-02, Master of Science Thesis*, Texas A& M University, 2002.

[23] P. Barford, J. Kline, D. Plonka, and A. Ron, "A signal analysis of traffic anomalies," in *IMW '02 Proceedings of the 2nd ACM SIGCOMM Workshop on Internet measurement*, pp. 71-82, 2002.

[24] S. S. Kim and A. Reddy, "Detecting traffic anomalies at the source through aggregate analysis of packet header data," in *Proceedings of Networking*, 2004.

[25] Li, L., Gyungho Lee, "DDos attack detection and wavelets," in *Computer Communications and Networks, 2003. ICCCN 2003. Proceedings. The 12th International Conference*, pp.421-427, 20-22 Oct. 2003.

[26] K. Zheng, X. Wang, Y. Yang and S. Guo, "Detecting DDoS Attack With Hilbert-Huang Transformation," in *China Communications*, Beijing, China, pp. 126-133, 2011.

[27] N.E. Huang, Z. Shen, S.R. Long, M.C. Wu, H.H. Shih, Q. Zheng, N. Yen, C.C. Tung, and H.H. Liu, "The empirical mode decomposition and the Hilbert spectrum for non-linear and non-stationary time series analysis," *Proc. Roy. Soc.*, London. A, vol.454, pp. 903-995, 1998.

[28] J. Z. Zhang, B. T. Price, R. D. Adams and T. J. Knaga, "Detection of Involuntary Human Hand Motions Using Empirical Mode Decomposition and Hilbert-Huang Transform," in *Circuits and systems, MWSCAS 2008. 51st Midwest Symposium*, pp. 157-160, Aug. 2008.

[29] M. S. Taqqu, V. Teverovsky and W. Willinger "Estimators for long-range dependence: an expirical study," *Fractals*, vol. 3, no. 4, pp. 785-798, 1995.

[30] M. Tavallaee, E. Bagheri, W. Lu and A. Ghorbani, "A Detailed Analysis of the KDD CUP 99 Data Set," in *Computational Intelligence for Security and Defense Applications*, Ottawa, pp. 1-6, 2009.

[31] S. J. Stolfo, W. Fan, W. Lee, A. Prodromidis, and P. K. Chan, "Costbased modeling for fraud and intrusion detection: Results from the jam project," *DARPA Information Survivability Conference and Exposition, 2000. DISCEX '00. Proceedings* , vol. 02, pp. 130-144, 2000.

[32] R. P. Lippmann, D. J. Fried, I. Graf, J. W. Haines, K. R. Kendall, D. McClung, D. Weber, S. E. Webster, D. Wyschogrod, R. K. Cunningham, and M. A. Zissman, "Evaluating intrusion detection systems: The 1998 darpa off-line intrusion detection evaluation," *DARPA Information Survivability Conference and Exposition, 2000. DISCEX '00. Proceedings* , vol. 02, pp. 12-26, 2000.

[33] MIT Lincoln Labs, 1998 DARPA Intrusion Detection Evaluation. Available at: http://www.ll.mit.edu/mission/communications/ist/corpora/ideval/index.html, February 2008.

[34] KDD Cup 1999, Available at: http://kdd.ics.uci.edu/databases/kddcup99/task.html, Ocotber 2007.

[35] Kayacik, H. Gunes, A. Nur Zincir-Heywood, and Malcolm I. Heywood, "Selecting features for intrusion detection: A feature relevance analysis on KDD 99 intrusion detection datasets," in *Proceedings of the Third Annual Conference on Privacy, Security and Trust (PST-2005)*, 2005.

[36] X. Cheng, K. Xie and D. Wang, "Network traffic anomaly detection based on self-similarity using HHT and wavelet transform," in *5th International Conference on Information Assurance and Security*, Baoding, China, pp. 710-713, 2009.

[37] John J. Shynk (2012). *Probability, Random Variables, and Random Processes: Theory and Signal Processing Applications*. Wiley-Interscience.

Appendices

APPENDIX A: TESTING RESULTS USING METHOD 1

Window size was 1000 sample points, the moving interval was 500 sample points, the total window number was 987. The detection criterion was: if $H_W \leq H_{Wth1}$, set 'c' (Decision) = 1 (No Attacks); if $H_W > H_{Wth1}$, set 'c' (Decision) = 0 (With DoS Attacks). Test results are listed in the following table:

Column a: Window index number

Column b: H_W (Weighted Self-similarity)

Column c: Decision (1: No Attacks; 0 With DoS Attacks)

Column d: True/False (1: True; 0: False)

a	b	c	d
1	17.95	1	1
2	17.32	1	1
3	13.11	1	1
4	16.77	1	1
5	13.51	1	1
6	15.50	1	1
7	20.06	0	0
8	21.70	0	0
9	24.90	0	0
10	18.94	1	1
11	17.29	1	1
12	17.04	1	1
13	13.46	1	1
14	14.99	1	1
15	23.51	0	1
16	28.22	0	1
17	25.04	0	1
18	25.72	0	1
19	31.92	0	1
20	31.15	0	1
21	25.08	0	1
22	25.62	0	1
23	24.48	0	1
24	28.08	0	0
25	15.23	1	1
26	22.17	0	0
27	15.87	1	1
28	14.67	1	1
29	19.73	1	1
30	24.33	0	0
31	31.13	0	1
32	26.64	0	1
33	29.72	0	0
34	22.52	0	0
35	17.54	1	1
36	15.85	1	1
37	21.51	0	0
38	26.13	0	1
39	27.05	0	1
40	23.41	0	0
41	15.51	1	1
42	13.78	1	1
43	16.25	1	1
44	24.10	0	0
45	21.61	0	0
46	24.77	0	0
47	22.12	0	0
48	14.55	1	1
49	15.64	1	1
50	15.70	1	1
51	17.29	1	1
52	17.89	1	1
53	18.86	1	1
54	24.41	0	0
55	21.92	0	0
56	17.33	1	1
57	14.45	1	1
58	16.63	1	1
59	19.62	1	1
60	18.31	1	1
61	18.70	1	1
62	16.59	1	1
63	15.31	1	0
64	16.12	1	0
65	17.36	1	1
66	15.55	1	1
67	15.48	1	1
68	14.33	1	1
69	15.34	1	1
70	20.76	0	0
71	24.33	0	0
72	21.05	0	0
73	17.37	1	1
74	17.17	1	1
75	14.87	1	1
76	15.86	1	1
77	16.14	1	1
78	17.69	1	1
79	17.60	1	0
80	20.55	0	1
81	22.86	0	1
82	19.68	1	0
83	22.65	0	0
84	22.43	0	0
85	23.03	0	0
86	24.38	0	1
87	24.92	0	1
88	22.03	0	1
89	26.68	0	1
90	27.26	0	1
91	31.37	0	1
92	28.41	0	1
93	19.06	1	0
94	25.36	0	1
95	27.85	0	1
96	24.34	0	1
97	21.93	0	1
98	27.73	0	1
99	22.15	0	1
100	24.26	0	1
101	21.44	0	1
102	26.34	0	1
103	19.44	1	0
104	19.26	1	0
105	24.63	0	0
106	21.08	0	0
107	25.73	0	1
108	24.07	0	1
109	23.34	0	1
110	21.14	0	1
111	21.57	0	1
112	15.10	1	0
113	14.29	1	0
114	15.82	1	0
115	20.29	0	1
116	18.90	1	0
117	16.09	1	0
118	17.55	1	0
119	19.60	1	0
120	16.98	1	0
121	18.74	1	0
122	17.88	1	0
123	15.65	1	0
124	21.53	0	1
125	18.54	1	0
126	11.24	1	0
127	18.16	1	0
128	20.70	0	1
129	20.61	0	1
130	12.70	1	0
131	11.18	1	0
132	11.79	1	0
133	12.05	1	0
134	13.76	1	0
135	15.83	1	0
136	9.49	1	0
137	8.98	1	0
138	12.21	1	0
139	11.58	1	0
140	9.98	1	0
141	10.57	1	0
142	14.36	1	0
143	14.58	1	0
144	10.06	1	0
145	9.05	1	0
146	13.87	1	0
147	15.10	1	0
148	18.40	1	0
149	22.19	0	1
150	24.64	0	0
151	26.52	0	0
152	26.42	0	1
153	26.32	0	1
154	21.39	0	0
155	16.15	1	1
156	22.92	0	1
157	17.04	1	0
158	18.75	1	0
159	12.22	1	1
160	16.02	1	1
161	19.99	1	1
162	18.41	1	1
163	19.49	1	1
164	17.07	1	1
165	19.75	1	0
166	19.11	1	0
167	16.00	1	1
168	16.20	1	1
169	15.76	1	1
170	15.86	1	1
171	18.02	1	1
172	20.91	0	0
173	24.67	0	1
174	27.06	0	1
175	15.27	1	1
176	24.41	0	0
177	16.44	1	1
178	15.66	1	1
179	21.99	0	0
180	22.88	0	0
181	25.40	0	0
182	24.91	0	0
183	27.40	0	0
184	26.44	0	1
185	23.09	0	1
186	29.87	0	1
187	18.08	1	0
188	28.76	0	1
189	25.57	0	1
190	23.19	0	1
191	20.26	0	1
192	20.65	0	1
193	28.17	0	1
194	28.85	0	1
195	27.98	0	1
196	30.69	0	1
197	37.87	0	1
198	27.28	0	1
199	22.02	0	1
200	23.58	0	1
201	24.44	0	1
202	28.56	0	1
203	26.54	0	1

204	30.79	0	1
205	25.12	0	1
206	37.69	0	1
207	26.40	0	1
208	28.54	0	1
209	15.82	1	1
210	14.13	1	1
211	17.56	1	1
212	19.77	1	1
213	17.07	1	1
214	15.86	1	1
215	21.87	0	0
216	20.35	0	1
217	17.03	1	0
218	14.91	1	0
219	13.69	1	0
220	14.18	1	0
221	14.95	1	0
222	14.68	1	0
223	11.98	1	0
224	20.73	0	1
225	16.53	1	0
226	14.37	1	0
227	15.16	1	0
228	20.30	0	1
229	17.92	1	0
230	17.33	1	0
231	14.84	1	0
232	14.52	1	0
233	13.20	1	0
234	14.69	1	0
235	16.06	1	0
236	18.05	1	0
237	16.62	1	0
238	14.11	1	0
239	15.95	1	0
240	14.46	1	0
241	9.94	1	0
242	12.25	1	0
243	15.61	1	0
244	7.97	1	0
245	15.34	1	0
246	8.10	1	0
247	14.27	1	0
248	7.82	1	0
249	10.82	1	0
250	6.21	1	0
251	12.85	1	0
252	6.60	1	0
253	6.99	1	0
254	11.17	1	0

255	14.77	1	0
256	19.85	1	0
257	20.37	0	1
258	30.60	0	1
259	28.37	0	1
260	24.18	0	1
261	26.71	0	1
262	31.08	0	1
263	25.98	0	1
264	23.34	0	1
265	22.41	0	1
266	29.28	0	1
267	24.73	0	1
268	24.61	0	1
269	21.55	0	1
270	28.01	0	1
271	31.25	0	1
272	24.45	0	1
273	24.32	0	1
274	30.00	0	1
275	27.85	0	0
276	16.91	1	1
277	15.88	1	1
278	15.09	1	1
279	16.29	1	1
280	21.07	0	1
281	17.99	1	0
282	24.33	0	0
283	27.23	0	1
284	23.76	0	1
285	18.21	1	0
286	25.44	0	1
287	31.23	0	1
288	20.99	0	0
289	21.02	0	0
290	19.01	1	1
291	30.73	0	0
292	22.37	0	0
293	19.90	1	1
294	20.17	0	0
295	19.38	1	1
296	20.11	0	0
297	20.87	0	0
298	26.20	0	1
299	20.86	0	1
300	24.18	0	1
301	23.85	0	1
302	21.71	0	1
303	22.48	0	1
304	23.24	0	1
305	20.31	0	1

306	20.91	0	1
307	27.38	0	1
308	25.14	0	1
309	21.67	0	1
310	26.66	0	1
311	27.68	0	1
312	22.27	0	1
313	25.34	0	1
314	22.62	0	1
315	23.17	0	1
316	23.46	0	1
317	31.11	0	1
318	27.17	0	1
319	24.09	0	1
320	18.02	1	0
321	16.18	1	0
322	19.94	1	0
323	24.98	0	1
324	25.08	0	1
325	18.09	1	0
326	24.59	0	1
327	27.04	0	1
328	19.25	1	0
329	22.63	0	1
330	21.58	0	1
331	24.01	0	1
332	24.22	0	1
333	22.05	0	1
334	22.65	0	1
335	24.21	0	1
336	26.12	0	1
337	29.45	0	1
338	25.74	0	1
339	19.88	1	0
340	22.65	0	1
341	22.50	0	1
342	22.97	0	1
343	23.25	0	1
344	29.05	0	1
345	27.64	0	1
346	25.36	0	1
347	22.88	0	1
348	27.59	0	1
349	23.22	0	1
350	27.22	0	1
351	29.49	0	1
352	21.94	0	1
353	22.90	0	1
354	20.82	0	1
355	29.65	0	1
356	23.86	0	1

357	25.57	0	1
358	31.89	0	1
359	27.31	0	1
360	27.36	0	1
361	20.54	0	1
362	28.71	0	1
363	22.95	0	1
364	31.10	0	1
365	28.29	0	1
366	25.12	0	1
367	24.02	0	1
368	31.94	0	1
369	28.16	0	1
370	23.26	0	1
371	27.29	0	1
372	24.07	0	1
373	21.48	0	1
374	32.45	0	1
375	22.73	0	1
376	25.75	0	1
377	20.53	0	1
378	21.89	0	1
379	20.62	0	1
380	23.42	0	1
381	25.62	0	1
382	24.01	0	1
383	23.86	0	1
384	20.96	0	1
385	19.58	1	0
386	28.52	0	1
387	20.54	0	1
388	27.21	0	1
389	28.09	0	1
390	21.22	0	1
391	20.03	0	1
392	23.15	0	1
393	19.06	1	0
394	17.63	1	0
395	18.11	1	0
396	19.37	1	0
397	17.55	1	0
398	19.83	1	0
399	22.71	0	1
400	18.12	1	0
401	20.24	0	1
402	16.51	1	0
403	20.71	0	1
404	22.29	0	1
405	22.53	0	1
406	22.09	0	1
407	19.69	1	0

408	17.17	1	0
409	15.32	1	0
410	16.45	1	0
411	15.55	1	0
412	18.28	1	0
413	21.37	0	1
414	18.55	1	0
415	16.29	1	0
416	15.69	1	0
417	17.05	1	0
418	20.74	0	1
419	19.84	1	0
420	18.26	1	0
421	16.48	1	0
422	21.66	0	1
423	21.15	0	1
424	21.98	0	1
425	25.15	0	1
426	25.49	0	1
427	18.05	1	0
428	17.14	1	0
429	19.43	1	0
430	16.70	1	0
431	20.14	0	1
432	20.29	0	1
433	21.20	0	1
434	19.73	1	0
435	18.06	1	0
436	22.09	0	1
437	20.35	0	1
438	21.52	0	1
439	20.72	0	1
440	21.78	0	1
441	22.48	0	1
442	20.30	0	1
443	17.48	1	0
444	17.57	1	0
445	21.64	0	1
446	20.82	0	1
447	18.73	1	0
448	19.93	1	0
449	23.53	0	1
450	19.38	1	0
451	16.95	1	0
452	28.49	0	1
453	20.86	0	1
454	17.83	1	0
455	20.75	0	1
456	18.67	1	0
457	24.45	0	1
458	19.10	1	0
459	16.03	1	0
460	18.27	1	0
461	18.91	1	0
462	18.83	1	0
463	20.70	0	1
464	22.85	0	1
465	23.19	0	1
466	19.66	1	0
467	20.16	0	1
468	18.40	1	0
469	19.97	1	0
470	23.77	0	1
471	18.65	1	0
472	18.22	1	0
473	19.19	1	0
474	18.46	1	0
475	19.43	1	0
476	19.49	1	0
477	17.91	1	0
478	15.90	1	0
479	15.36	1	0
480	17.89	1	0
481	17.83	1	0
482	18.16	1	0
483	22.99	0	1
484	20.54	0	1
485	22.37	0	1
486	24.95	0	1
487	22.36	0	1
488	20.40	0	1
489	16.98	1	0
490	16.20	1	0
491	21.55	0	1
492	23.20	0	1
493	18.18	1	0
494	19.32	1	0
495	20.10	0	1
496	20.31	0	1
497	23.12	0	1
498	19.60	1	0
499	20.01	0	1
500	18.76	1	0
501	18.32	1	0
502	21.89	0	1
503	18.19	1	0
504	22.10	0	1
505	13.99	1	0
506	21.01	0	1
507	24.42	0	1
508	26.55	0	1
509	16.48	1	0
510	23.76	0	1
511	21.31	0	1
512	19.35	1	0
513	18.10	1	0
514	22.55	0	1
515	21.98	0	1
516	20.66	0	1
517	23.81	0	1
518	28.53	0	1
519	20.98	0	1
520	20.22	0	1
521	23.72	0	1
522	21.36	0	1
523	15.31	1	0
524	21.14	0	1
525	22.81	0	1
526	25.11	0	1
527	29.10	0	1
528	26.97	0	1
529	20.55	0	1
530	22.74	0	1
531	24.69	0	1
532	21.75	0	1
533	29.01	0	1
534	23.70	0	1
535	27.11	0	1
536	33.06	0	1
537	22.20	0	1
538	19.83	1	0
539	21.37	0	1
540	23.54	0	1
541	25.63	0	1
542	21.13	0	1
543	28.04	0	1
544	18.48	1	0
545	22.53	0	1
546	26.91	0	1
547	28.12	0	1
548	25.06	0	1
549	23.21	0	1
550	20.67	0	1
551	21.46	0	1
552	22.12	0	1
553	19.36	1	0
554	29.31	0	1
555	25.90	0	1
556	25.73	0	1
557	25.08	0	1
558	34.57	0	1
559	23.75	0	1
560	22.44	0	1
561	28.40	0	1
562	23.76	0	1
563	26.87	0	1
564	22.06	0	1
565	21.56	0	1
566	19.23	1	0
567	26.56	0	1
568	25.36	0	1
569	28.03	0	1
570	35.95	0	1
571	30.87	0	1
572	20.21	0	1
573	24.39	0	1
574	26.58	0	1
575	25.80	0	1
576	22.34	0	1
577	21.94	0	1
578	21.91	0	1
579	25.25	0	1
580	24.73	0	1
581	23.29	0	1
582	23.64	0	1
583	32.30	0	1
584	26.64	0	1
585	23.56	0	1
586	29.20	0	1
587	27.39	0	1
588	17.56	1	0
589	20.92	0	1
590	27.77	0	1
591	24.11	0	1
592	23.42	0	1
593	20.11	0	1
594	22.87	0	1
595	22.38	0	1
596	21.30	0	1
597	19.94	1	0
598	29.23	0	1
599	21.78	0	1
600	27.86	0	1
601	24.62	0	1
602	25.62	0	1
603	21.04	0	1
604	18.47	1	0
605	26.11	0	1
606	25.35	0	1
607	20.24	0	1
608	24.56	0	1
609	25.56	0	1
610	27.11	0	1
611	28.11	0	1

612	20.15	0	1
613	23.96	0	1
614	30.11	0	1
615	26.51	0	1
616	24.16	0	1
617	23.93	0	1
618	22.33	0	1
619	29.37	0	1
620	27.32	0	1
621	31.61	0	1
622	24.06	0	1
623	20.12	0	1
624	26.66	0	1
625	20.16	0	1
626	19.01	1	0
627	23.69	0	1
628	25.06	0	1
629	31.41	0	1
630	28.24	0	1
631	23.93	0	1
632	20.25	0	1
633	26.98	0	1
634	18.01	1	0
635	29.85	0	1
636	22.43	0	1
637	23.37	0	1
638	24.04	0	1
639	20.04	0	1
640	23.95	0	1
641	27.31	0	1
642	30.49	0	1
643	27.42	0	1
644	22.96	0	1
645	24.49	0	1
646	24.71	0	1
647	26.31	0	1
648	26.27	0	1
649	28.81	0	1
650	28.72	0	1
651	20.75	0	1
652	26.82	0	1
653	24.00	0	1
654	28.15	0	1
655	28.29	0	1
656	37.07	0	1
657	28.14	0	1
658	23.50	0	1
659	29.42	0	1
660	22.94	0	1
661	23.30	0	1
662	24.36	0	1

663	19.35	1	0
664	33.85	0	1
665	19.94	1	0
666	20.50	0	1
667	23.84	0	1
668	27.68	0	1
669	23.65	0	1
670	23.70	0	1
671	17.46	1	0
672	27.26	0	1
673	20.42	0	1
674	26.24	0	1
675	27.73	0	1
676	27.71	0	1
677	23.95	0	1
678	22.56	0	1
679	27.63	0	1
680	23.87	0	1
681	18.19	1	0
682	20.72	0	1
683	29.73	0	1
684	23.34	0	1
685	23.37	0	1
686	26.35	0	1
687	20.99	0	0
688	21.14	0	0
689	27.96	0	1
690	22.01	0	1
691	19.50	1	0
692	24.71	0	1
693	25.33	0	1
694	25.85	0	1
695	32.99	0	0
696	30.41	0	0
697	24.31	0	0
698	24.40	0	1
699	18.99	1	0
700	18.36	1	0
701	20.39	0	1
702	16.27	1	0
703	15.48	1	0
704	16.03	1	0
705	15.32	1	0
706	14.49	1	0
707	23.04	0	1
708	18.03	1	0
709	29.24	0	1
710	20.74	0	1
711	17.40	1	0
712	17.13	1	0
713	19.28	1	0

714	15.37	1	0
715	17.04	1	0
716	15.02	1	0
717	16.90	1	0
718	18.14	1	0
719	21.07	0	1
720	17.85	1	0
721	16.78	1	0
722	17.40	1	0
723	15.84	1	0
724	18.13	1	0
725	20.68	0	1
726	17.45	1	0
727	19.52	1	0
728	13.79	1	0
729	13.49	1	0
730	14.92	1	0
731	13.76	1	0
732	22.17	0	1
733	21.19	0	1
734	17.91	1	0
735	17.26	1	0
736	18.57	1	0
737	17.03	1	0
738	15.88	1	0
739	15.59	1	0
740	23.37	0	1
741	25.62	0	1
742	28.50	0	1
743	28.67	0	1
744	25.07	0	1
745	26.11	0	1
746	9.30	1	0
747	6.35	1	0
748	7.08	1	0
749	11.28	1	0
750	9.31	1	0
751	14.05	1	0
752	5.25	1	0
753	8.53	1	0
754	13.22	1	0
755	10.40	1	0
756	14.37	1	0
757	9.63	1	0
758	9.90	1	0
759	9.80	1	0
760	15.48	1	0
761	15.91	1	0
762	10.86	1	0
763	8.94	1	0
764	7.73	1	0

765	7.25	1	0
766	6.70	1	0
767	11.88	1	0
768	13.24	1	0
769	12.35	1	0
770	4.39	1	0
771	6.50	1	0
772	16.08	1	0
773	19.70	1	0
774	24.31	0	1
775	21.64	0	1
776	16.33	1	0
777	11.75	1	0
778	18.46	1	0
779	15.47	1	0
780	5.51	1	0
781	11.94	1	0
782	14.26	1	0
783	17.01	1	0
784	13.50	1	0
785	6.08	1	0
786	7.45	1	0
787	8.86	1	0
788	9.14	1	0
789	13.69	1	0
790	10.14	1	0
791	6.76	1	0
792	4.53	1	0
793	16.51	1	0
794	23.10	0	1
795	27.67	0	1
796	23.72	0	1
797	25.78	0	1
798	20.40	0	1
799	25.55	0	1
800	23.40	0	1
801	19.79	1	0
802	20.96	0	1
803	22.32	0	1
804	22.07	0	1
805	20.84	0	1
806	27.79	0	1
807	28.53	0	1
808	24.37	0	1
809	24.93	0	1
810	22.49	0	1
811	22.35	0	1
812	19.28	1	0
813	20.18	0	1
814	21.73	0	1
815	19.37	1	0

816	21.72	0	1
817	19.03	1	0
818	21.07	0	1
819	19.91	1	0
820	23.23	0	1
821	21.25	0	1
822	24.42	0	1
823	16.62	1	0
824	31.76	0	1
825	24.35	0	1
826	18.42	1	0
827	17.12	1	0
828	16.07	1	0
829	14.39	1	0
830	14.41	1	0
831	16.78	1	0
832	16.05	1	0
833	20.95	0	1
834	23.44	0	1
835	27.99	0	1
836	24.99	0	1
837	23.39	0	1
838	33.27	0	1
839	32.08	0	1
840	34.23	0	1
841	37.07	0	1
842	36.75	0	1
843	33.04	0	1
844	34.13	0	1
845	27.59	0	1
846	35.06	0	1
847	25.77	0	1
848	26.84	0	1
849	36.85	0	1
850	25.81	0	1
851	22.62	0	1
852	26.12	0	1
853	23.47	0	1
854	25.99	0	1
855	21.20	0	1
856	21.61	0	1
857	22.55	0	1
858	24.13	0	1

859	26.82	0	1
860	29.73	0	1
861	37.49	0	1
862	33.75	0	1
863	27.83	0	1
864	29.00	0	1
865	37.71	0	1
866	42.53	0	1
867	34.24	0	1
868	41.59	0	1
869	26.74	0	1
870	31.23	0	1
871	25.20	0	1
872	31.13	0	1
873	30.90	0	1
874	39.45	0	1
875	40.09	0	1
876	28.60	0	1
877	30.87	0	1
878	26.60	0	1
879	29.90	0	1
880	21.07	0	1
881	21.60	0	1
882	21.51	0	1
883	22.51	0	1
884	24.08	0	1
885	25.39	0	1
886	24.73	0	1
887	23.82	0	1
888	22.64	0	1
889	29.36	0	1
890	25.01	0	1
891	37.45	0	1
892	21.89	0	1
893	25.09	0	1
894	25.79	0	1
895	37.69	0	1
896	25.10	0	1
897	25.37	0	1
898	25.48	0	1
899	21.33	0	1
900	25.50	0	1
901	18.62	1	1

902	23.75	0	0
903	21.34	0	0
904	27.66	0	1
905	23.43	0	1
906	26.06	0	0
907	24.04	0	0
908	22.37	0	0
909	21.88	0	0
910	30.94	0	0
911	18.48	1	0
912	18.37	1	0
913	23.11	0	1
914	20.66	0	0
915	18.89	1	1
916	19.77	1	1
917	24.63	0	1
918	20.31	0	1
919	14.94	1	0
920	17.14	1	0
921	21.37	0	1
922	13.35	1	0
923	14.04	1	0
924	15.68	1	0
925	17.46	1	0
926	15.97	1	0
927	15.31	1	0
928	11.08	1	0
929	14.07	1	0
930	17.31	1	0
931	17.36	1	0
932	18.18	1	0
933	17.93	1	0
934	19.69	1	0
935	16.08	1	0
936	14.86	1	0
937	17.84	1	0
938	13.73	1	0
939	14.31	1	0
940	24.67	0	1
941	18.27	1	0
942	14.12	1	0
943	16.02	1	0
944	15.00	1	0

945	11.69	1	0
946	14.25	1	0
947	15.80	1	0
948	7.79	1	0
949	7.60	1	0
950	7.41	1	0
951	13.20	1	0
952	4.89	1	0
953	12.07	1	0
954	7.08	1	0
955	13.32	1	0
956	9.99	1	0
957	12.72	1	0
958	6.74	1	0
959	13.25	1	0
960	32.03	0	1
961	23.39	0	1
962	20.22	0	1
963	19.15	1	1
964	19.40	1	1
965	16.95	1	1
966	15.16	1	1
967	15.48	1	1
968	16.59	1	1
969	13.53	1	1
970	14.37	1	0
971	15.75	1	0
972	14.28	1	0
973	18.56	1	0
974	31.38	0	1
975	25.38	0	1
976	21.65	0	1
977	29.10	0	1
978	19.76	1	0
979	27.72	0	1
980	22.19	0	1
981	26.59	0	1
982	30.36	0	1
983	23.96	0	0
984	25.79	0	0
985	16.46	1	1
986	11.43	1	1
987	13.26	1	1

APPENDIX B: TESTING RESULTS USING METHOD 2

Window size was 200 sample points, the moving interval was 200 sample points, the total window number was 2469. The detection criterion was: if $d \leq d_{th}$, set ‘c’ (Decision) = 1 (No Attacks); if $d > d_{th}$, set ‘c’ (Decision) = 0 (With DoS Attacks). Test results are listed in the following table:

Column a: Window index number

Column b: Pearson’s Distance ‘d’

Column c: Decision (1: No Attacks; 0 With DoS Attacks)

Column d: True/False (1: True; 0: False)

a	b	c	d
1	0.28	1	1
2	0.30	1	1
3	0.47	1	1
4	0.46	1	1
5	0.44	1	1
6	0.39	1	1
7	0.39	1	1
8	0.35	1	1
9	0.28	1	1
10	0.30	1	1
11	0.29	1	1
12	0.29	1	1
13	0.32	1	1
14	0.29	1	1
15	0.22	1	1
16	0.28	1	1
17	0.36	1	1
18	0.34	1	1
19	0.35	1	1
20	0.44	1	1
21	0.84	0	0
22	0.36	1	1
23	0.21	1	1
24	0.31	1	1
25	0.34	1	1
26	0.24	1	1
27	0.37	1	1
28	0.27	1	1
29	0.32	1	1
30	0.33	1	1
31	0.28	1	1
32	0.30	1	1
33	0.36	1	1
34	0.29	1	1
35	0.36	1	1
36	0.35	1	1
37	0.40	1	1
38	0.48	1	1
39	0.96	0	1
40	0.90	0	1
41	1.00	0	1
42	0.96	0	1
43	0.88	0	1
44	0.85	0	1
45	1.00	0	1
46	0.97	0	1
47	0.97	0	1
48	0.99	0	1
49	0.82	0	1
50	0.98	0	1
51	0.96	0	1
52	0.80	0	1
53	0.79	0	1
54	0.59	0	1
55	0.82	0	1
56	0.43	1	0
57	0.68	0	1
58	0.97	0	1
59	0.50	0	0
60	0.40	1	1
61	0.36	1	1
62	0.31	1	1
63	0.31	1	1
64	0.32	1	1
65	0.31	1	1
66	0.39	1	1
67	0.24	1	1
68	0.30	1	1
69	0.33	1	1
70	0.38	1	1
71	0.25	1	1
72	0.23	1	1
73	0.26	1	1
74	0.41	1	1
75	0.39	1	1
76	0.25	1	1
77	0.30	1	1
78	0.49	1	1
79	0.86	0	1
80	0.36	1	0
81	0.37	1	1
82	0.28	1	1
83	0.42	1	1
84	0.26	1	1
85	0.32	1	1
86	0.29	1	1
87	0.32	1	1
88	0.26	1	1
89	0.37	1	1
90	0.29	1	1
91	0.31	1	1
92	0.52	0	0
93	0.33	1	1
94	0.31	1	1
95	0.29	1	1
96	0.43	1	1
97	0.91	0	1
98	0.47	1	1
99	0.31	1	1
100	0.37	1	1
101	0.34	1	1
102	0.89	0	0
103	0.24	1	1
104	0.27	1	1
105	0.33	1	1
106	0.28	1	1
107	0.30	1	1
108	0.26	1	1
109	0.37	1	1
110	0.34	1	1
111	0.27	1	1
112	0.47	1	1
113	0.54	0	0
114	0.53	0	0
115	0.87	0	0
116	0.29	1	1
117	0.41	1	1
118	0.32	1	1
119	0.35	1	1
120	0.26	1	1
121	0.35	1	1
122	0.36	1	1
123	0.30	1	1
124	0.26	1	1
125	0.40	1	1
126	0.34	1	1
127	0.30	1	1
128	0.51	0	0
129	0.30	1	1
130	0.29	1	1
131	0.47	1	1
132	0.52	0	0
133	0.44	1	1
134	0.77	0	0
135	0.35	1	1
136	0.74	0	0
137	0.73	0	0
138	0.30	1	1
139	0.34	1	1
140	0.27	1	1
141	0.33	1	1
142	0.41	1	1
143	0.32	1	1
144	0.29	1	1
145	0.33	1	1
146	0.41	1	1
147	0.34	1	1
148	0.36	1	1
149	0.28	1	1
150	0.35	1	1
151	0.46	1	1
152	0.37	1	1
153	0.31	1	1
154	0.44	1	1
155	0.35	1	1
156	0.38	1	1
157	0.53	0	0
158	0.44	1	1
159	0.71	0	1
160	0.72	0	0
161	0.41	1	1
162	0.38	1	1
163	0.29	1	1
164	0.33	1	1
165	0.31	1	1
166	0.27	1	1
167	0.45	1	1
168	0.34	1	1
169	0.39	1	1
170	0.42	1	1
171	0.22	1	1
172	0.39	1	1
173	0.40	1	1
174	0.25	1	1
175	0.28	1	1
176	0.77	0	0
177	0.32	1	1
178	0.50	1	1
179	0.36	1	1
180	0.62	0	0
181	0.61	0	0
182	0.38	1	1
183	0.34	1	1
184	0.32	1	1
185	0.32	1	1
186	0.32	1	1
187	0.34	1	1
188	0.31	1	1
189	0.45	1	1
190	0.27	1	1
191	0.37	1	1
192	0.58	0	0
193	0.31	1	1
194	0.37	1	1
195	0.28	1	1
196	0.23	1	1
197	0.38	1	1
198	0.61	0	0
199	0.53	0	1
200	0.33	1	0
201	0.39	1	0
202	0.35	1	0
203	0.27	1	0

204	0.39	1	0
205	0.76	0	0
206	0.87	0	0
207	0.62	0	0
208	0.80	0	0
209	0.62	0	0
210	0.57	0	0
211	0.83	0	0
212	0.56	0	0
213	0.73	0	0
214	0.86	0	0
215	0.83	0	0
216	0.98	0	1
217	0.81	0	1
218	0.82	0	1
219	0.83	0	1
220	0.84	0	1
221	0.81	0	1
222	0.63	0	1
223	0.84	0	1
224	0.69	0	1
225	0.75	0	1
226	0.86	0	1
227	0.82	0	1
228	0.65	0	1
229	1.00	0	1
230	0.80	0	1
231	0.60	0	1
232	0.84	0	1
233	0.80	0	1
234	0.83	0	1
235	0.83	0	1
236	0.96	0	1
237	0.83	0	1
238	0.82	0	1
239	0.99	0	1
240	0.94	0	1
241	0.80	0	1
242	0.68	0	1
243	0.82	0	1
244	0.81	0	1
245	0.95	0	1
246	0.84	0	1
247	0.81	0	1
248	0.67	0	1
249	0.80	0	1
250	0.66	0	1
251	0.86	0	1
252	0.84	0	1
253	0.85	0	1
254	1.00	0	1

255	0.53	0	1
256	0.29	1	0
257	0.29	1	0
258	0.37	1	0
259	0.32	1	0
260	0.41	1	0
261	0.44	1	1
262	0.81	0	0
263	0.70	0	0
264	0.96	0	0
265	0.47	1	1
266	1.00	0	0
267	0.71	0	0
268	0.73	0	1
269	0.52	0	1
270	0.41	1	0
271	0.58	0	1
272	0.60	0	1
273	0.81	0	1
274	0.69	0	1
275	0.71	0	1
276	0.54	0	1
277	0.63	0	1
278	0.62	0	1
279	0.71	0	1
280	0.44	1	0
281	0.49	1	0
282	0.55	0	1
283	0.59	0	1
284	0.73	0	1
285	0.67	0	1
286	0.56	0	1
287	0.59	0	1
288	0.82	0	1
289	0.59	0	1
290	0.64	0	1
291	0.48	1	0
292	0.39	1	0
293	0.86	0	1
294	0.65	0	1
295	0.48	1	0
296	0.66	0	1
297	0.57	0	1
298	0.75	0	1
299	0.75	0	1
300	0.63	0	1
301	0.58	0	1
302	0.56	0	1
303	0.50	1	0
304	0.48	1	0
305	0.61	0	1

306	0.60	0	1
307	0.65	0	1
308	0.63	0	1
309	0.74	0	1
310	0.60	0	1
311	0.71	0	1
312	0.76	0	1
313	0.38	1	0
314	0.56	0	1
315	0.50	0	1
316	0.72	0	1
317	0.80	0	1
318	0.74	0	1
319	0.51	0	1
320	0.79	0	1
321	0.72	0	1
322	0.66	0	1
323	0.96	0	1
324	0.50	1	0
325	0.48	1	0
326	0.47	1	0
327	0.47	1	0
328	0.56	0	1
329	0.64	0	1
330	0.60	0	1
331	0.60	0	1
332	0.74	0	1
333	0.74	0	1
334	0.85	0	1
335	0.45	1	0
336	0.62	0	1
337	0.97	0	1
338	0.45	1	0
339	0.89	0	1
340	0.65	0	1
341	0.88	0	1
342	0.62	0	1
343	0.61	0	1
344	0.87	0	1
345	0.37	1	0
346	0.53	0	1
347	0.98	0	1
348	0.82	0	1
349	0.67	0	1
350	0.66	0	1
351	0.45	1	0
352	0.58	0	1
353	0.47	1	0
354	0.68	0	1
355	0.49	1	0
356	0.65	0	1

357	0.42	1	0
358	0.78	0	1
359	0.43	1	0
360	0.78	0	1
361	0.85	0	1
362	0.97	0	1
363	0.98	0	1
364	0.52	0	1
365	0.58	0	1
366	0.96	0	1
367	0.77	0	1
368	0.85	0	1
369	0.64	0	1
370	0.56	0	1
371	0.55	0	1
372	0.38	1	1
373	0.96	0	0
374	0.58	0	0
375	0.78	0	0
376	0.59	0	0
377	0.80	0	0
378	0.31	1	1
379	0.33	1	1
380	0.35	1	1
381	0.89	0	1
382	0.53	0	1
383	0.32	1	0
384	0.94	0	0
385	0.75	0	0
386	0.87	0	0
387	0.47	1	1
388	0.44	1	1
389	0.31	1	1
390	0.48	1	1
391	0.47	1	0
392	0.56	0	1
393	0.48	1	0
394	0.71	0	0
395	0.46	1	1
396	0.31	1	1
397	0.27	1	1
398	0.28	1	1
399	0.28	1	1
400	0.30	1	1
401	0.39	1	1
402	0.29	1	1
403	0.31	1	1
404	0.36	1	1
405	0.39	1	1
406	0.33	1	1
407	0.32	1	1

408	0.25	1	1
409	0.38	1	1
410	0.46	1	1
411	0.25	1	1
412	0.48	1	1
413	0.48	1	1
414	0.52	0	0
415	0.76	0	1
416	0.83	0	0
417	0.59	0	0
418	0.26	1	1
419	0.35	1	1
420	0.31	1	1
421	0.35	1	1
422	0.34	1	1
423	0.34	1	1
424	0.46	1	1
425	0.32	1	1
426	0.34	1	1
427	0.42	1	1
428	0.29	1	1
429	0.32	1	1
430	0.29	1	1
431	0.41	1	1
432	0.64	0	0
433	0.91	0	1
434	0.95	0	1
435	0.95	0	0
436	0.40	1	1
437	0.39	1	1
438	0.33	1	1
439	0.31	1	1
440	0.44	1	1
441	0.31	1	1
442	0.36	1	1
443	0.35	1	1
444	0.34	1	1
445	0.24	1	1
446	0.30	1	1
447	0.26	1	1
448	0.42	1	1
449	0.47	1	1
450	0.39	1	1
451	0.48	1	1
452	0.34	1	1
453	0.33	1	1
454	0.36	1	1
455	0.52	0	0
456	0.33	1	1
457	0.72	0	0
458	0.43	1	1

459	0.96	0	0
460	0.90	0	0
461	0.95	0	1
462	0.91	0	1
463	0.89	0	1
464	0.88	0	1
465	0.94	0	1
466	0.90	0	1
467	0.98	0	1
468	0.94	0	1
469	0.89	0	1
470	0.96	0	1
471	0.96	0	1
472	0.94	0	1
473	0.95	0	1
474	0.97	0	1
475	0.97	0	1
476	0.96	0	1
477	0.92	0	1
478	0.99	0	1
479	0.96	0	1
480	0.96	0	1
481	0.96	0	1
482	0.97	0	1
483	0.93	0	1
484	0.96	0	1
485	0.82	0	1
486	0.95	0	1
487	0.94	0	1
488	0.99	0	1
489	0.96	0	1
490	0.91	0	1
491	0.96	0	1
492	0.64	0	1
493	0.81	0	1
494	0.69	0	1
495	0.99	0	1
496	0.81	0	1
497	0.78	0	1
498	0.90	0	1
499	0.83	0	1
500	0.69	0	1
501	0.86	0	1
502	0.82	0	1
503	0.79	0	1
504	0.73	0	1
505	0.90	0	1
506	0.81	0	1
507	0.87	0	1
508	0.82	0	1
509	0.82	0	1

510	0.64	0	1
511	0.55	0	1
512	0.58	0	1
513	0.79	0	1
514	1.00	0	1
515	0.80	0	1
516	0.80	0	1
517	0.79	0	1
518	0.85	0	1
519	0.99	0	1
520	0.72	0	0
521	0.60	0	0
522	0.43	1	1
523	0.40	1	1
524	0.26	1	1
525	0.29	1	1
526	0.38	1	1
527	0.37	1	1
528	0.28	1	1
529	0.32	1	1
530	0.28	1	1
531	0.26	1	1
532	0.31	1	1
533	0.25	1	1
534	0.36	1	1
535	0.40	1	1
536	0.42	1	1
537	0.33	1	1
538	0.28	1	1
539	0.44	1	1
540	0.44	1	1
541	0.57	0	1
542	0.86	0	1
543	0.54	0	1
544	0.76	0	1
545	0.67	0	1
546	0.54	0	1
547	0.66	0	1
548	0.71	0	1
549	0.64	0	1
550	0.70	0	1
551	0.47	1	0
552	0.42	1	0
553	0.57	0	1
554	0.59	0	1
555	0.66	0	1
556	0.85	0	1
557	0.63	0	1
558	0.62	0	1
559	0.80	0	1
560	0.69	0	1

561	0.68	0	1
562	0.54	0	1
563	0.54	0	1
564	0.57	0	1
565	0.63	0	1
566	0.68	0	1
567	0.62	0	1
568	0.72	0	1
569	0.72	0	1
570	0.87	0	1
571	0.55	0	1
572	0.74	0	1
573	0.66	0	1
574	0.74	0	1
575	0.61	0	1
576	0.60	0	1
577	0.63	0	1
578	0.62	0	1
579	0.78	0	1
580	0.59	0	1
581	0.56	0	1
582	0.58	0	1
583	0.38	1	0
584	0.59	0	1
585	0.52	0	1
586	0.47	1	0
587	0.57	0	1
588	0.44	1	0
589	0.61	0	1
590	0.87	0	1
591	0.67	0	1
592	0.46	1	0
593	0.39	1	0
594	0.83	0	1
595	0.64	0	1
596	0.79	0	1
597	0.57	0	1
598	0.61	0	1
599	0.51	0	1
600	0.61	0	1
601	0.56	0	1
602	0.71	0	1
603	0.55	0	1
604	0.83	0	1
605	0.82	0	1
606	0.70	0	1
607	0.53	0	1
608	0.54	0	1
609	0.56	0	1
610	0.55	0	1
611	0.89	0	1

612	0.70	0	1
613	0.76	0	1
614	0.72	0	1
615	0.73	0	1
616	0.58	0	1
617	0.84	0	1
618	0.59	0	1
619	0.60	0	1
620	0.58	0	1
621	0.87	0	1
622	0.88	0	1
623	0.65	0	1
624	0.58	0	1
625	0.76	0	1
626	0.55	0	1
627	1.00	0	1
628	0.97	0	1
629	0.78	0	1
630	0.51	0	1
631	0.76	0	1
632	0.67	0	1
633	0.67	0	1
634	0.68	0	1
635	0.61	0	1
636	0.71	0	1
637	0.46	1	0
638	0.62	0	1
639	0.75	0	1
640	0.83	0	1
641	0.96	0	1
642	0.59	0	1
643	0.61	0	1
644	0.81	0	1
645	0.77	0	1
646	0.85	0	1
647	0.76	0	1
648	0.99	0	1
649	0.82	0	1
650	0.99	0	1
651	0.96	0	1
652	0.98	0	1
653	0.97	0	1
654	0.97	0	1
655	0.99	0	1
656	0.95	0	1
657	0.96	0	1
658	0.97	0	1
659	0.98	0	1
660	1.00	0	1
661	0.92	0	1
662	0.99	0	1

663	0.82	0	1
664	0.84	0	1
665	0.82	0	1
666	0.64	0	1
667	0.86	0	1
668	0.82	0	1
669	0.83	0	1
670	0.63	0	1
671	0.85	0	1
672	0.80	0	1
673	0.87	0	1
674	0.83	0	1
675	0.83	0	1
676	0.82	0	1
677	0.90	0	1
678	0.58	0	1
679	0.83	0	1
680	0.99	0	1
681	0.82	0	1
682	0.86	0	1
683	0.52	0	1
684	0.31	1	0
685	0.42	1	1
686	0.97	0	0
687	0.47	1	1
688	0.49	1	1
689	0.32	1	1
690	0.25	1	1
691	0.42	1	1
692	0.34	1	1
693	0.33	1	1
694	0.32	1	1
695	0.29	1	1
696	0.27	1	1
697	0.34	1	1
698	0.29	1	1
699	0.29	1	1
700	0.38	1	1
701	0.50	0	0
702	0.79	0	1
703	0.91	0	0
704	0.92	0	0
705	0.63	0	0
706	0.98	0	0
707	0.71	0	0
708	0.96	0	1
709	0.96	0	1
710	0.87	0	0
711	0.54	0	0
712	0.60	0	0
713	0.71	0	1

714	0.79	0	0
715	0.61	0	0
716	0.76	0	0
717	0.88	0	1
718	0.94	0	0
719	0.84	0	0
720	0.72	0	0
721	0.55	0	0
722	0.51	0	0
723	0.89	0	0
724	0.62	0	0
725	0.77	0	0
726	0.54	0	0
727	0.44	1	1
728	0.39	1	1
729	0.38	1	1
730	0.47	1	1
731	0.87	0	0
732	0.96	0	0
733	0.65	0	0
734	0.49	1	1
735	0.54	0	0
736	0.58	0	0
737	0.68	0	0
738	0.57	0	0
739	0.70	0	0
740	0.64	0	0
741	0.61	0	0
742	0.49	1	1
743	0.78	0	0
744	0.49	1	1
745	0.71	0	0
746	0.62	0	0
747	1.00	0	1
748	0.93	0	0
749	0.90	0	0
750	0.89	0	1
751	0.82	0	1
752	0.90	0	1
753	0.86	0	1
754	0.98	0	1
755	0.88	0	1
756	0.93	0	1
757	0.94	0	1
758	0.91	0	1
759	0.87	0	1
760	0.79	0	1
761	0.98	0	1
762	0.99	0	1
763	0.85	0	1
764	0.98	0	1

765	0.97	0	1
766	0.89	0	1
767	0.84	0	1
768	0.96	0	1
769	0.99	0	1
770	0.97	0	1
771	0.90	0	1
772	0.77	0	1
773	0.92	0	1
774	0.90	0	1
775	0.99	0	1
776	0.92	0	1
777	0.92	0	1
778	0.99	0	1
779	0.96	0	1
780	0.89	0	1
781	0.98	0	1
782	0.95	0	1
783	0.98	0	1
784	0.96	0	1
785	0.93	0	1
786	0.95	0	1
787	0.88	0	1
788	1.00	0	1
789	0.86	0	1
790	0.98	0	1
791	0.98	0	1
792	0.96	0	1
793	0.97	0	1
794	0.96	0	1
795	0.98	0	1
796	0.96	0	1
797	0.81	0	1
798	0.95	0	1
799	0.93	0	1
800	0.97	0	1
801	0.95	0	1
802	0.88	0	1
803	0.94	0	1
804	0.89	0	1
805	0.95	0	1
806	0.95	0	1
807	1.00	0	1
808	0.93	0	1
809	0.96	0	1
810	0.95	0	1
811	0.93	0	1
812	0.96	0	1
813	0.96	0	1
814	0.88	0	1
815	0.90	0	1

816	0.95	0	1
817	1.00	0	1
818	0.91	0	1
819	0.92	0	1
820	0.96	0	1
821	0.92	0	1
822	0.94	0	1
823	1.00	0	1
824	0.98	0	1
825	0.89	0	1
826	0.91	0	1
827	0.94	0	1
828	0.99	0	1
829	0.95	0	1
830	0.91	0	1
831	0.97	0	1
832	0.94	0	1
833	0.93	0	1
834	0.92	0	1
835	0.85	0	1
836	0.80	0	1
837	0.92	0	1
838	0.83	0	1
839	0.81	0	1
840	0.84	0	1
841	0.78	0	1
842	0.96	0	1
843	0.88	0	1
844	0.98	0	1
845	0.82	0	1
846	0.76	0	1
847	0.98	0	1
848	0.83	0	1
849	0.93	0	1
850	0.86	0	1
851	0.80	0	1
852	0.53	0	1
853	0.55	0	1
854	0.97	0	1
855	0.96	0	1
856	0.81	0	1
857	0.62	0	1
858	0.83	0	1
859	0.74	0	1
860	0.60	0	1
861	0.99	0	1
862	0.83	0	1
863	0.65	0	1
864	0.81	0	1
865	0.87	0	1
866	0.64	0	1
867	0.82	0	1
868	0.47	1	0
869	0.88	0	1
870	0.77	0	1
871	0.78	0	1
872	0.85	0	1
873	0.83	0	1
874	0.82	0	1
875	0.92	0	1
876	0.66	0	1
877	0.90	0	1
878	0.58	0	1
879	0.90	0	1
880	0.60	0	1
881	0.78	0	1
882	0.95	0	1
883	0.97	0	1
884	0.90	0	1
885	0.84	0	1
886	0.88	0	1
887	0.80	0	1
888	0.81	0	1
889	0.83	0	1
890	0.87	0	1
891	0.81	0	1
892	0.82	0	1
893	0.57	0	1
894	0.87	0	1
895	0.80	0	1
896	0.68	0	1
897	0.90	0	1
898	0.86	0	1
899	0.81	0	1
900	0.57	0	1
901	0.71	0	1
902	0.57	0	1
903	0.63	0	1
904	0.87	0	1
905	0.78	0	1
906	0.61	0	1
907	0.64	0	1
908	0.81	0	1
909	0.80	0	1
910	0.81	0	1
911	0.82	0	1
912	0.78	0	1
913	0.82	0	1
914	0.84	0	1
915	0.98	0	1
916	0.82	0	1
917	0.86	0	1
918	0.69	0	1
919	0.83	0	1
920	0.89	0	1
921	0.97	0	1
922	1.00	0	1
923	0.90	0	1
924	0.92	0	1
925	0.96	0	1
926	0.99	0	1
927	0.97	0	1
928	0.97	0	1
929	0.96	0	1
930	0.99	0	1
931	0.94	0	1
932	0.98	0	1
933	0.94	0	1
934	0.92	0	1
935	0.94	0	1
936	0.97	0	1
937	0.91	0	1
938	0.92	0	1
939	0.95	0	1
940	0.96	0	1
941	0.99	0	1
942	0.99	0	1
943	0.89	0	1
944	0.95	0	1
945	0.98	0	1
946	0.95	0	1
947	0.91	0	1
948	0.98	0	1
949	0.96	0	1
950	0.95	0	1
951	0.99	0	1
952	0.91	0	1
953	0.90	0	1
954	0.95	0	1
955	0.91	0	1
956	0.99	0	1
957	0.95	0	1
958	0.96	0	1
959	0.91	0	1
960	0.96	0	1
961	0.95	0	1
962	0.98	0	1
963	0.99	0	1
964	0.93	0	1
965	0.95	0	1
966	0.97	0	1
967	0.98	0	1
968	0.96	0	1
969	0.93	0	1
970	0.97	0	1
971	0.93	0	1
972	0.98	0	1
973	0.95	0	1
974	0.91	0	1
975	0.94	0	1
976	0.95	0	1
977	0.98	0	1
978	0.86	0	1
979	0.98	0	1
980	0.85	0	1
981	0.92	0	1
982	0.96	0	1
983	0.99	0	1
984	0.87	0	1
985	0.97	0	1
986	0.96	0	1
987	0.94	0	1
988	0.89	0	1
989	0.95	0	1
990	0.86	0	1
991	0.99	0	1
992	0.93	0	1
993	0.94	0	1
994	0.92	0	1
995	0.99	0	1
996	0.93	0	1
997	0.94	0	1
998	0.98	0	1
999	0.94	0	1
1000	0.99	0	1
1001	0.96	0	1
1002	0.88	0	1
1003	0.96	0	1
1004	0.95	0	1
1005	0.97	0	1
1006	0.88	0	1
1007	0.94	0	1
1008	0.94	0	1
1009	0.84	0	1
1010	0.97	0	1
1011	0.92	0	1
1012	0.96	0	1
1013	0.90	0	1
1014	0.90	0	1
1015	0.88	0	1
1016	0.99	0	1
1017	0.95	0	1
1018	0.94	0	1
1019	0.94	0	1

1020	0.99	0	1
1021	0.93	0	1
1022	0.91	0	1
1023	0.93	0	1
1024	0.95	0	1
1025	0.90	0	1
1026	0.97	0	1
1027	0.95	0	1
1028	0.89	0	1
1029	0.93	0	1
1030	0.91	0	1
1031	0.92	0	1
1032	0.93	0	1
1033	0.95	0	1
1034	0.91	0	1
1035	0.89	0	1
1036	0.91	0	1
1037	0.96	0	1
1038	0.96	0	1
1039	0.97	0	1
1040	0.85	0	1
1041	0.95	0	1
1042	0.88	0	1
1043	0.91	0	1
1044	0.92	0	1
1045	0.90	0	1
1046	0.95	0	1
1047	0.94	0	1
1048	0.97	0	1
1049	0.95	0	1
1050	0.87	0	1
1051	0.97	0	1
1052	0.92	0	1
1053	1.00	0	1
1054	0.88	0	1
1055	0.94	0	1
1056	0.91	0	1
1057	0.94	0	1
1058	0.99	0	1
1059	0.94	0	1
1060	0.89	0	1
1061	0.96	0	1
1062	0.93	0	1
1063	0.94	0	1
1064	0.95	0	1
1065	0.92	0	1
1066	0.93	0	1
1067	0.90	0	1
1068	0.93	0	1
1069	0.93	0	1
1070	0.94	0	1

1071	0.96	0	1
1072	0.93	0	1
1073	0.96	0	1
1074	0.95	0	1
1075	0.94	0	1
1076	0.98	0	1
1077	0.83	0	1
1078	0.98	0	1
1079	0.95	0	1
1080	0.95	0	1
1081	0.95	0	1
1082	0.95	0	1
1083	0.96	0	1
1084	0.92	0	1
1085	0.98	0	1
1086	0.93	0	1
1087	0.97	0	1
1088	0.98	0	1
1089	0.96	0	1
1090	0.92	0	1
1091	0.94	0	1
1092	0.90	0	1
1093	0.93	0	1
1094	1.00	0	1
1095	0.92	0	1
1096	0.92	0	1
1097	0.95	0	1
1098	0.87	0	1
1099	0.93	0	1
1100	0.91	0	1
1101	0.97	0	1
1102	0.92	0	1
1103	0.97	0	1
1104	0.95	0	1
1105	0.97	0	1
1106	0.96	0	1
1107	0.90	0	1
1108	0.99	0	1
1109	0.87	0	1
1110	0.97	0	1
1111	0.88	0	1
1112	0.96	0	1
1113	0.93	0	1
1114	0.94	0	1
1115	0.88	0	1
1116	0.93	0	1
1117	0.83	0	1
1118	0.95	0	1
1119	0.96	0	1
1120	0.96	0	1
1121	0.80	0	1

1122	0.93	0	1
1123	0.99	0	1
1124	0.99	0	1
1125	0.88	0	1
1126	0.98	0	1
1127	0.95	0	1
1128	0.92	0	1
1129	0.93	0	1
1130	0.96	0	1
1131	0.88	0	1
1132	0.98	0	1
1133	0.95	0	1
1134	0.92	0	1
1135	0.97	0	1
1136	0.93	0	1
1137	0.98	0	1
1138	0.94	0	1
1139	0.83	0	1
1140	1.00	0	1
1141	0.98	0	1
1142	0.93	0	1
1143	0.88	0	1
1144	0.93	0	1
1145	0.95	0	1
1146	0.95	0	1
1147	0.98	0	1
1148	0.93	0	1
1149	0.92	0	1
1150	0.94	0	1
1151	0.91	0	1
1152	0.90	0	1
1153	0.94	0	1
1154	0.95	0	1
1155	0.91	0	1
1156	1.00	0	1
1157	0.91	0	1
1158	0.99	0	1
1159	0.95	0	1
1160	0.94	0	1
1161	0.91	0	1
1162	0.97	0	1
1163	0.96	0	1
1164	0.92	0	1
1165	0.95	0	1
1166	0.88	0	1
1167	0.91	0	1
1168	0.99	0	1
1169	0.97	0	1
1170	0.93	0	1
1171	0.96	0	1
1172	0.94	0	1

1173	0.99	0	1
1174	0.97	0	1
1175	0.92	0	1
1176	0.92	0	1
1177	0.94	0	1
1178	0.96	0	1
1179	0.92	0	1
1180	0.98	0	1
1181	0.90	0	1
1182	0.95	0	1
1183	0.92	0	1
1184	0.94	0	1
1185	0.97	0	1
1186	0.92	0	1
1187	0.89	0	1
1188	1.00	0	1
1189	0.99	0	1
1190	0.97	0	1
1191	0.91	0	1
1192	0.95	0	1
1193	0.99	0	1
1194	0.98	0	1
1195	0.94	0	1
1196	0.98	0	1
1197	0.99	0	1
1198	0.96	0	1
1199	0.98	0	1
1200	0.88	0	1
1201	0.89	0	1
1202	0.94	0	1
1203	0.93	0	1
1204	0.88	0	1
1205	0.89	0	1
1206	0.95	0	1
1207	0.92	0	1
1208	0.94	0	1
1209	0.90	0	1
1210	0.88	0	1
1211	0.97	0	1
1212	0.99	0	1
1213	0.95	0	1
1214	0.95	0	1
1215	0.92	0	1
1216	0.93	0	1
1217	0.97	0	1
1218	0.98	0	1
1219	0.94	0	1
1220	0.96	0	1
1221	0.99	0	1
1222	0.98	0	1
1223	0.97	0	1

1224	0.92	0	1
1225	0.88	0	1
1226	0.98	0	1
1227	0.93	0	1
1228	0.96	0	1
1229	0.91	0	1
1230	0.87	0	1
1231	0.99	0	1
1232	0.98	0	1
1233	0.92	0	1
1234	0.93	0	1
1235	0.89	0	1
1236	0.93	0	1
1237	0.91	0	1
1238	0.96	0	1
1239	0.97	0	1
1240	0.87	0	1
1241	0.90	0	1
1242	0.87	0	1
1243	0.92	0	1
1244	0.97	0	1
1245	0.97	0	1
1246	0.95	0	1
1247	0.95	0	1
1248	0.96	0	1
1249	0.95	0	1
1250	0.84	0	1
1251	0.93	0	1
1252	0.91	0	1
1253	0.91	0	1
1254	0.99	0	1
1255	0.91	0	1
1256	0.91	0	1
1257	0.95	0	1
1258	0.87	0	1
1259	0.97	0	1
1260	0.89	0	1
1261	0.99	0	1
1262	0.96	0	1
1263	0.93	0	1
1264	0.97	0	1
1265	0.93	0	1
1266	0.88	0	1
1267	0.97	0	1
1268	0.88	0	1
1269	0.95	0	1
1270	0.98	0	1
1271	0.92	0	1
1272	0.92	0	1
1273	0.95	0	1
1274	0.99	0	1

1275	0.97	0	1
1276	0.98	0	1
1277	0.83	0	1
1278	0.96	0	1
1279	0.93	0	1
1280	0.92	0	1
1281	0.97	0	1
1282	0.93	0	1
1283	0.96	0	1
1284	0.93	0	1
1285	1.00	0	1
1286	0.88	0	1
1287	0.98	0	1
1288	0.95	0	1
1289	0.95	0	1
1290	0.97	0	1
1291	0.90	0	1
1292	0.88	0	1
1293	0.94	0	1
1294	0.90	0	1
1295	0.90	0	1
1296	0.94	0	1
1297	0.95	0	1
1298	0.96	0	1
1299	0.95	0	1
1300	0.99	0	1
1301	0.95	0	1
1302	0.81	0	1
1303	0.81	0	1
1304	0.86	0	1
1305	0.88	0	1
1306	0.82	0	1
1307	0.98	0	1
1308	0.92	0	1
1309	0.91	0	1
1310	0.95	0	1
1311	0.97	0	1
1312	0.82	0	1
1313	0.97	0	1
1314	0.82	0	1
1315	0.80	0	1
1316	0.89	0	1
1317	0.94	0	1
1318	0.99	0	1
1319	0.99	0	1
1320	0.94	0	1
1321	0.96	0	1
1322	0.99	0	1
1323	1.00	0	1
1324	0.92	0	1
1325	0.82	0	1

1326	0.97	0	1
1327	0.92	0	1
1328	0.82	0	1
1329	0.84	0	1
1330	0.94	0	1
1331	0.99	0	1
1332	0.85	0	1
1333	0.61	0	1
1334	0.86	0	1
1335	0.94	0	1
1336	0.99	0	1
1337	0.93	0	1
1338	0.87	0	1
1339	0.99	0	1
1340	0.79	0	1
1341	0.96	0	1
1342	0.96	0	1
1343	0.89	0	1
1344	0.85	0	1
1345	0.86	0	1
1346	0.92	0	1
1347	0.97	0	1
1348	0.93	0	1
1349	0.62	0	1
1350	0.91	0	1
1351	0.96	0	1
1352	0.76	0	1
1353	0.89	0	1
1354	0.89	0	1
1355	0.86	0	1
1356	0.81	0	1
1357	0.98	0	1
1358	0.92	0	1
1359	0.82	0	1
1360	0.89	0	1
1361	0.65	0	1
1362	0.92	0	1
1363	0.97	0	1
1364	0.82	0	1
1365	0.83	0	1
1366	0.98	0	1
1367	0.84	0	1
1368	0.98	0	1
1369	0.97	0	1
1370	1.00	0	1
1371	0.80	0	1
1372	0.94	0	1
1373	0.91	0	1
1374	0.66	0	1
1375	0.94	0	1
1376	0.84	0	1

1377	0.88	0	1
1378	1.00	0	1
1379	0.84	0	1
1380	0.87	0	1
1381	0.68	0	1
1382	0.84	0	1
1383	0.66	0	1
1384	0.93	0	1
1385	0.90	0	1
1386	0.53	0	1
1387	0.80	0	1
1388	0.97	0	1
1389	0.84	0	1
1390	0.56	0	1
1391	0.92	0	1
1392	0.89	0	1
1393	0.95	0	1
1394	0.96	0	1
1395	0.92	0	1
1396	0.81	0	1
1397	0.68	0	1
1398	0.82	0	1
1399	0.93	0	1
1400	0.90	0	1
1401	0.65	0	1
1402	0.81	0	1
1403	0.84	0	1
1404	0.67	0	1
1405	0.81	0	1
1406	0.87	0	1
1407	0.90	0	1
1408	0.84	0	1
1409	0.83	0	1
1410	0.82	0	1
1411	0.82	0	1
1412	0.90	0	1
1413	0.82	0	1
1414	0.89	0	1
1415	0.84	0	1
1416	0.71	0	1
1417	0.96	0	1
1418	0.94	0	1
1419	0.82	0	1
1420	0.82	0	1
1421	0.85	0	1
1422	0.87	0	1
1423	0.96	0	1
1424	0.92	0	1
1425	0.82	0	1
1426	0.81	0	1
1427	0.93	0	1

1428	0.70	0	1
1429	0.97	0	1
1430	0.96	0	1
1431	0.60	0	1
1432	0.53	0	1
1433	0.96	0	1
1434	0.89	0	1
1435	0.80	0	1
1436	0.86	0	1
1437	0.72	0	1
1438	0.93	0	1
1439	0.87	0	1
1440	0.90	0	1
1441	0.94	0	1
1442	0.95	0	1
1443	0.83	0	1
1444	0.84	0	1
1445	0.90	0	1
1446	0.79	0	1
1447	0.94	0	1
1448	0.82	0	1
1449	0.89	0	1
1450	0.95	0	1
1451	0.85	0	1
1452	0.93	0	1
1453	0.92	0	1
1454	0.73	0	1
1455	0.89	0	1
1456	0.94	0	1
1457	1.00	0	1
1458	0.68	0	1
1459	0.88	0	1
1460	1.00	0	1
1461	1.00	0	1
1462	1.00	0	1
1463	0.93	0	1
1464	0.87	0	1
1465	0.84	0	1
1466	0.86	0	1
1467	0.95	0	1
1468	0.97	0	1
1469	0.96	0	1
1470	0.84	0	1
1471	0.90	0	1
1472	0.85	0	1
1473	0.99	0	1
1474	0.94	0	1
1475	0.81	0	1
1476	0.96	0	1
1477	0.79	0	1
1478	0.72	0	1

1479	0.56	0	1
1480	0.97	0	1
1481	0.83	0	1
1482	0.93	0	1
1483	0.81	0	1
1484	0.88	0	1
1485	0.99	0	1
1486	0.83	0	1
1487	0.84	0	1
1488	0.83	0	1
1489	0.92	0	1
1490	0.55	0	1
1491	0.96	0	1
1492	0.83	0	1
1493	0.93	0	1
1494	0.91	0	1
1495	0.94	0	1
1496	0.96	0	1
1497	1.00	0	1
1498	0.96	0	1
1499	0.96	0	1
1500	0.89	0	1
1501	0.99	0	1
1502	0.82	0	1
1503	0.84	0	1
1504	0.92	0	1
1505	0.79	0	1
1506	0.93	0	1
1507	0.97	0	1
1508	0.55	0	1
1509	0.84	0	1
1510	0.97	0	1
1511	0.85	0	1
1512	0.85	0	1
1513	0.86	0	1
1514	0.96	0	1
1515	0.73	0	1
1516	0.54	0	1
1517	0.90	0	1
1518	0.89	0	1
1519	0.82	0	1
1520	0.84	0	1
1521	0.99	0	1
1522	0.95	0	1
1523	0.78	0	1
1524	0.81	0	1
1525	0.78	0	1
1526	0.81	0	1
1527	0.95	0	1
1528	0.83	0	1
1529	0.95	0	1

1530	0.98	0	1
1531	0.93	0	1
1532	0.65	0	1
1533	0.93	0	1
1534	0.96	0	1
1535	0.83	0	1
1536	0.98	0	1
1537	0.80	0	1
1538	0.93	0	1
1539	0.76	0	1
1540	0.75	0	1
1541	0.85	0	1
1542	0.93	0	1
1543	0.80	0	1
1544	0.91	0	1
1545	0.60	0	1
1546	0.89	0	1
1547	0.98	0	1
1548	0.85	0	1
1549	0.86	0	1
1550	0.93	0	1
1551	0.87	0	1
1552	0.93	0	1
1553	0.96	0	1
1554	0.84	0	1
1555	0.94	0	1
1556	0.80	0	1
1557	0.85	0	1
1558	0.79	0	1
1559	0.95	0	1
1560	0.81	0	1
1561	0.99	0	1
1562	0.91	0	1
1563	0.96	0	1
1564	0.62	0	1
1565	0.82	0	1
1566	0.84	0	1
1567	0.85	0	1
1568	0.98	0	1
1569	0.96	0	1
1570	0.82	0	1
1571	0.62	0	1
1572	0.85	0	1
1573	0.95	0	1
1574	0.91	0	1
1575	0.89	0	1
1576	0.81	0	1
1577	0.93	0	1
1578	0.85	0	1
1579	0.96	0	1
1580	0.98	0	1

1581	0.85	0	1
1582	0.82	0	1
1583	0.98	0	1
1584	0.97	0	1
1585	0.83	0	1
1586	0.92	0	1
1587	0.84	0	1
1588	0.66	0	1
1589	0.96	0	1
1590	0.84	0	1
1591	0.80	0	1
1592	0.93	0	1
1593	0.90	0	1
1594	0.89	0	1
1595	0.83	0	1
1596	0.82	0	1
1597	0.77	0	1
1598	0.89	0	1
1599	0.80	0	1
1600	0.82	0	1
1601	0.96	0	1
1602	0.97	0	1
1603	0.86	0	1
1604	0.87	0	1
1605	0.94	0	1
1606	0.97	0	1
1607	0.61	0	1
1608	0.89	0	1
1609	0.84	0	1
1610	0.98	0	1
1611	0.88	0	1
1612	0.93	0	1
1613	0.71	0	1
1614	0.58	0	1
1615	0.95	0	1
1616	0.82	0	1
1617	0.85	0	1
1618	0.59	0	1
1619	0.87	0	1
1620	0.99	0	1
1621	0.99	0	1
1622	0.97	0	1
1623	0.96	0	1
1624	0.65	0	1
1625	0.87	0	1
1626	0.97	0	1
1627	0.83	0	1
1628	0.90	0	1
1629	0.94	0	1
1630	0.86	0	1
1631	0.82	0	1

1632	0.66	0	1
1633	0.99	0	1
1634	0.65	0	1
1635	0.90	0	1
1636	0.95	0	1
1637	0.97	0	1
1638	0.85	0	1
1639	0.89	0	1
1640	0.80	0	1
1641	0.90	0	1
1642	0.83	0	1
1643	0.87	0	1
1644	0.90	0	1
1645	0.82	0	1
1646	0.89	0	1
1647	0.64	0	1
1648	0.88	0	1
1649	0.83	0	1
1650	0.89	0	1
1651	0.80	0	1
1652	0.82	0	1
1653	0.93	0	1
1654	0.80	0	1
1655	0.82	0	1
1656	0.85	0	1
1657	0.60	0	1
1658	0.81	0	1
1659	0.91	0	1
1660	0.84	0	1
1661	0.92	0	1
1662	0.88	0	1
1663	0.90	0	1
1664	0.88	0	1
1665	0.84	0	1
1666	0.99	0	1
1667	0.97	0	1
1668	0.81	0	1
1669	0.81	0	1
1670	0.93	0	1
1671	0.96	0	1
1672	0.97	0	1
1673	0.79	0	1
1674	0.83	0	1
1675	0.90	0	1
1676	0.86	0	1
1677	0.94	0	1
1678	0.90	0	1
1679	0.60	0	1
1680	0.93	0	1
1681	0.89	0	1
1682	0.86	0	1

1683	0.69	0	1
1684	0.94	0	1
1685	0.83	0	1
1686	0.82	0	1
1687	0.93	0	1
1688	0.81	0	1
1689	1.00	0	1
1690	0.81	0	1
1691	0.81	0	1
1692	1.00	0	1
1693	0.86	0	1
1694	0.80	0	1
1695	0.93	0	1
1696	0.62	0	1
1697	0.82	0	1
1698	0.88	0	1
1699	0.80	0	1
1700	0.82	0	1
1701	0.70	0	1
1702	0.97	0	1
1703	0.97	0	1
1704	0.79	0	1
1705	0.64	0	1
1706	0.85	0	1
1707	0.84	0	1
1708	0.97	0	1
1709	0.79	0	1
1710	0.99	0	1
1711	0.81	0	1
1712	0.98	0	1
1713	0.81	0	1
1714	0.82	0	1
1715	0.98	0	1
1716	0.44	1	1
1717	0.39	1	1
1718	0.67	0	0
1719	0.89	0	0
1720	0.75	0	0
1721	0.60	0	0
1722	0.39	1	1
1723	0.66	0	0
1724	0.86	0	0
1725	0.81	0	1
1726	0.36	1	1
1727	0.86	0	0
1728	0.61	0	0
1729	0.37	1	1
1730	0.81	0	1
1731	0.79	0	0
1732	0.77	0	0
1733	0.73	0	0

1734	0.85	0	1
1735	0.61	0	0
1736	0.29	1	1
1737	0.41	1	1
1738	0.42	1	1
1739	0.39	1	1
1740	0.84	0	0
1741	0.45	1	1
1742	0.42	1	1
1743	0.36	1	1
1744	0.38	1	1
1745	0.52	0	0
1746	0.96	0	0
1747	0.73	0	1
1748	0.42	1	0
1749	0.48	1	0
1750	0.38	1	0
1751	0.32	1	0
1752	0.29	1	0
1753	0.38	1	0
1754	0.33	1	0
1755	0.34	1	0
1756	0.29	1	0
1757	0.44	1	0
1758	0.51	0	1
1759	0.42	1	0
1760	0.54	0	1
1761	0.46	1	0
1762	0.38	1	0
1763	0.33	1	0
1764	0.35	1	0
1765	0.45	1	0
1766	0.41	1	0
1767	0.35	1	0
1768	0.39	1	0
1769	0.44	1	0
1770	0.51	0	1
1771	0.54	0	1
1772	0.53	0	1
1773	0.56	0	1
1774	0.34	1	0
1775	0.27	1	0
1776	0.39	1	0
1777	0.30	1	0
1778	0.31	1	0
1779	0.25	1	0
1780	0.46	1	0
1781	0.71	0	1
1782	0.61	0	1
1783	0.42	1	0
1784	0.47	1	0

1785	0.37	1	0
1786	0.29	1	0
1787	0.30	1	0
1788	0.43	1	0
1789	0.31	1	0
1790	0.33	1	0
1791	0.47	1	0
1792	0.50	1	0
1793	0.34	1	0
1794	0.46	1	0
1795	0.56	0	1
1796	0.31	1	0
1797	0.30	1	0
1798	0.44	1	0
1799	0.36	1	0
1800	0.30	1	0
1801	0.38	1	0
1802	0.41	1	0
1803	0.42	1	0
1804	0.40	1	0
1805	0.51	0	1
1806	0.37	1	0
1807	0.57	0	1
1808	0.45	1	0
1809	0.55	0	1
1810	0.46	1	0
1811	0.59	0	1
1812	0.70	0	1
1813	0.83	0	1
1814	0.69	0	1
1815	0.46	1	0
1816	0.64	0	1
1817	0.56	0	1
1818	0.42	1	0
1819	0.46	1	0
1820	0.50	1	0
1821	0.39	1	0
1822	0.43	1	0
1823	0.52	0	1
1824	0.45	1	0
1825	0.42	1	0
1826	0.38	1	0
1827	0.40	1	0
1828	0.41	1	0
1829	0.47	1	0
1830	0.55	0	1
1831	0.47	1	0
1832	0.36	1	0
1833	0.37	1	0
1834	0.44	1	0
1835	0.39	1	0

1836	0.40	1	0
1837	0.29	1	0
1838	0.39	1	0
1839	0.55	0	1
1840	0.57	0	1
1841	0.65	0	1
1842	0.49	1	0
1843	0.40	1	0
1844	0.27	1	0
1845	0.32	1	0
1846	0.36	1	0
1847	0.38	1	0
1848	0.34	1	0
1849	0.93	0	1
1850	0.95	0	1
1851	0.87	0	1
1852	0.99	0	1
1853	0.40	1	0
1854	0.98	0	1
1855	0.97	0	1
1856	0.90	0	1
1857	0.98	0	1
1858	0.51	0	1
1859	0.31	1	1
1860	0.71	0	0
1861	0.59	0	0
1862	0.85	0	1
1863	0.93	0	1
1864	0.55	0	1
1865	0.57	0	1
1866	0.93	0	1
1867	0.53	0	1
1868	0.80	0	1
1869	0.57	0	1
1870	0.71	0	1
1871	0.69	0	1
1872	0.99	0	1
1873	0.57	0	1
1874	0.88	0	1
1875	0.97	0	1
1876	0.74	0	1
1877	0.88	0	1
1878	0.51	0	1
1879	0.71	0	1
1880	0.93	0	1
1881	0.89	0	1
1882	0.98	0	1
1883	0.84	0	1
1884	0.58	0	1
1885	0.80	0	1
1886	0.50	1	0

1887	0.94	0	1
1888	0.74	0	1
1889	0.54	0	1
1890	0.61	0	1
1891	0.56	0	1
1892	1.00	0	1
1893	0.61	0	1
1894	0.84	0	1
1895	0.61	0	1
1896	0.47	1	0
1897	0.53	0	1
1898	0.60	0	1
1899	0.56	0	1
1900	0.72	0	1
1901	0.90	0	1
1902	0.69	0	1
1903	0.53	0	1
1904	0.54	0	1
1905	0.91	0	1
1906	0.43	1	0
1907	0.98	0	1
1908	0.77	0	1
1909	0.99	0	1
1910	0.63	0	1
1911	0.96	0	1
1912	0.92	0	1
1913	1.00	0	1
1914	0.89	0	1
1915	0.64	0	1
1916	0.74	0	1
1917	0.99	0	1
1918	0.71	0	1
1919	0.71	0	1
1920	0.45	1	0
1921	0.55	0	1
1922	0.90	0	1
1923	0.64	0	1
1924	0.89	0	1
1925	0.74	0	1
1926	0.80	0	1
1927	0.95	0	1
1928	0.53	0	1
1929	0.55	0	1
1930	0.62	0	1
1931	0.83	0	1
1932	0.46	1	0
1933	0.99	0	1
1934	0.64	0	1
1935	0.85	0	1
1936	0.77	0	1
1937	0.74	0	1

1938	0.65	0	1
1939	0.56	0	1
1940	0.45	1	0
1941	0.63	0	1
1942	0.44	1	0
1943	0.55	0	1
1944	0.62	0	1
1945	0.42	1	0
1946	0.41	1	0
1947	0.59	0	1
1948	0.99	0	1
1949	0.64	0	1
1950	0.67	0	1
1951	0.84	0	1
1952	0.64	0	1
1953	0.64	0	1
1954	0.82	0	1
1955	0.84	0	1
1956	0.49	1	0
1957	0.51	0	1
1958	0.59	0	1
1959	0.65	0	1
1960	0.50	0	1
1961	0.60	0	1
1962	0.50	1	0
1963	0.53	0	1
1964	0.90	0	1
1965	0.71	0	1
1966	0.99	0	1
1967	0.90	0	1
1968	0.38	1	0
1969	0.61	0	1
1970	0.46	1	0
1971	0.59	0	1
1972	0.51	0	1
1973	0.49	1	0
1974	0.46	1	0
1975	0.53	0	1
1976	0.69	0	1
1977	0.96	0	1
1978	0.58	0	1
1979	0.52	0	1
1980	0.68	0	1
1981	0.53	0	1
1982	0.67	0	1
1983	0.89	0	1
1984	0.86	0	1
1985	0.45	1	1
1986	0.89	0	1
1987	0.78	0	1
1988	0.84	0	1

1989	0.90	0	1
1990	0.83	0	1
1991	0.79	0	1
1992	0.92	0	1
1993	0.89	0	1
1994	0.90	0	1
1995	0.90	0	1
1996	0.82	0	1
1997	0.99	0	1
1998	0.95	0	1
1999	0.79	0	1
2000	0.86	0	1
2001	0.98	0	1
2002	0.87	0	1
2003	0.85	0	1
2004	0.87	0	1
2005	0.96	0	1
2006	0.82	0	1
2007	0.87	0	1
2008	0.95	0	1
2009	0.79	0	1
2010	0.78	0	1
2011	0.91	0	1
2012	0.85	0	1
2013	0.96	0	1
2014	0.88	0	1
2015	0.81	0	1
2016	0.86	0	1
2017	0.81	0	1
2018	0.74	0	1
2019	0.75	0	1
2020	0.92	0	1
2021	0.94	0	1
2022	0.95	0	1
2023	0.94	0	1
2024	0.92	0	1
2025	0.91	0	1
2026	0.93	0	1
2027	0.93	0	1
2028	0.98	0	1
2029	0.84	0	1
2030	0.83	0	1
2031	0.89	0	1
2032	0.91	0	1
2033	0.91	0	1
2034	0.83	0	1
2035	0.83	0	1
2036	0.79	0	1
2037	0.83	0	1
2038	0.92	0	1
2039	0.88	0	1

2040	0.84	0	1
2041	0.97	0	1
2042	0.83	0	1
2043	0.96	0	1
2044	0.88	0	1
2045	0.97	0	1
2046	0.88	0	1
2047	0.91	0	1
2048	0.84	0	1
2049	0.81	0	1
2050	0.84	0	1
2051	0.72	0	1
2052	0.95	0	1
2053	0.92	0	1
2054	0.92	0	1
2055	0.92	0	1
2056	0.84	0	1
2057	0.86	0	1
2058	0.90	0	1
2059	0.90	0	1
2060	0.96	0	1
2061	0.84	0	1
2062	0.79	0	1
2063	0.88	0	1
2064	0.86	0	1
2065	0.83	0	1
2066	0.82	0	1
2067	0.88	0	1
2068	0.82	0	1
2069	0.77	0	1
2070	0.88	0	1
2071	0.83	0	1
2072	0.93	0	1
2073	0.80	0	1
2074	0.78	0	1
2075	0.76	0	1
2076	0.75	0	1
2077	0.63	0	1
2078	0.81	0	1
2079	0.66	0	1
2080	0.75	0	1
2081	0.67	0	1
2082	0.78	0	1
2083	0.82	0	1
2084	0.88	0	1
2085	0.91	0	1
2086	0.87	0	1
2087	0.86	0	1
2088	0.98	0	1
2089	0.89	0	1
2090	0.87	0	1

2091	0.96	0	1
2092	0.95	0	1
2093	0.99	0	1
2094	0.98	0	1
2095	0.98	0	1
2096	0.94	0	1
2097	0.99	0	1
2098	0.97	0	1
2099	0.77	0	1
2100	1.00	0	1
2101	0.99	0	1
2102	0.97	0	1
2103	0.97	0	1
2104	0.98	0	1
2105	0.96	0	1
2106	0.85	0	1
2107	0.85	0	1
2108	0.89	0	1
2109	0.98	0	1
2110	1.00	0	1
2111	0.98	0	1
2112	0.83	0	1
2113	0.83	0	1
2114	0.98	0	1
2115	0.78	0	1
2116	0.97	0	1
2117	0.90	0	1
2118	0.89	0	1
2119	0.83	0	1
2120	0.77	0	1
2121	0.96	0	1
2122	0.99	0	1
2123	0.88	0	1
2124	0.86	0	1
2125	0.76	0	1
2126	0.81	0	1
2127	0.84	0	1
2128	0.83	0	1
2129	0.98	0	1
2130	0.49	1	0
2131	0.95	0	1
2132	0.80	0	1
2133	0.96	0	1
2134	0.77	0	1
2135	0.92	0	1
2136	0.86	0	1
2137	0.86	0	1
2138	0.79	0	1
2139	0.64	0	1
2140	0.96	0	1
2141	0.85	0	1

2142	0.75	0	1
2143	0.91	0	1
2144	0.84	0	1
2145	0.96	0	1
2146	0.60	0	1
2147	0.82	0	1
2148	0.98	0	1
2149	0.79	0	1
2150	0.84	0	1
2151	0.98	0	1
2152	0.96	0	1
2153	1.00	0	1
2154	0.97	0	1
2155	0.63	0	1
2156	0.94	0	1
2157	0.85	0	1
2158	0.82	0	1
2159	0.54	0	1
2160	0.79	0	1
2161	0.99	0	1
2162	0.95	0	1
2163	0.81	0	1
2164	0.76	0	1
2165	0.96	0	1
2166	0.96	0	1
2167	0.80	0	1
2168	0.70	0	1
2169	0.99	0	1
2170	0.98	0	1
2171	0.85	0	1
2172	0.98	0	1
2173	0.90	0	1
2174	0.61	0	1
2175	0.82	0	1
2176	0.80	0	1
2177	0.99	0	1
2178	0.99	0	1
2179	0.79	0	1
2180	0.97	0	1
2181	0.83	0	1
2182	0.85	0	1
2183	0.83	0	1
2184	0.61	0	1
2185	0.98	0	1
2186	0.95	0	1
2187	0.78	0	1
2188	0.81	0	1
2189	0.78	0	1
2190	0.79	0	1
2191	0.88	0	1
2192	0.78	0	1

2193	0.82	0	1
2194	0.92	0	1
2195	0.83	0	1
2196	0.94	0	1
2197	0.98	0	1
2198	0.79	0	1
2199	0.81	0	1
2200	0.88	0	1
2201	0.83	0	1
2202	0.91	0	1
2203	0.85	0	1
2204	0.80	0	1
2205	0.79	0	1
2206	0.98	0	1
2207	0.75	0	1
2208	0.96	0	1
2209	0.93	0	1
2210	0.77	0	1
2211	0.78	0	1
2212	0.82	0	1
2213	0.82	0	1
2214	0.82	0	1
2215	0.99	0	1
2216	0.89	0	1
2217	0.63	0	1
2218	0.82	0	1
2219	0.98	0	1
2220	0.64	0	1
2221	0.83	0	1
2222	0.83	0	1
2223	0.72	0	1
2224	0.95	0	1
2225	0.81	0	1
2226	0.85	0	1
2227	0.98	0	1
2228	0.94	0	1
2229	0.72	0	1
2230	0.99	0	1
2231	0.84	0	1
2232	0.61	0	1
2233	0.95	0	1
2234	0.84	0	1
2235	0.81	0	1
2236	0.56	0	1
2237	0.99	0	1
2238	0.84	0	1
2239	0.99	0	1
2240	0.87	0	1
2241	0.91	0	1
2242	0.85	0	1
2243	0.95	0	1

2244	0.98	0	1
2245	0.86	0	1
2246	0.86	0	1
2247	0.95	0	1
2248	0.73	0	1
2249	0.97	0	1
2250	0.40	1	1
2251	0.37	1	1
2252	0.36	1	1
2253	0.35	1	1
2254	0.47	1	1
2255	0.89	0	0
2256	0.47	1	1
2257	0.51	0	0
2258	0.29	1	1
2259	0.35	1	1
2260	0.63	0	0
2261	0.70	0	0
2262	0.79	0	1
2263	0.77	0	1
2264	0.34	1	1
2265	0.31	1	1
2266	0.32	1	1
2267	0.47	1	1
2268	0.39	1	1
2269	0.41	1	1
2270	0.87	0	0
2271	0.46	1	1
2272	0.35	1	1
2273	0.35	1	1
2274	0.25	1	1
2275	0.52	0	0
2276	0.50	1	1
2277	0.84	0	0
2278	0.42	1	1
2279	0.68	0	0
2280	0.81	0	1
2281	0.65	0	0
2282	0.51	0	1
2283	0.35	1	1
2284	0.47	1	1
2285	0.35	1	1
2286	0.33	1	1
2287	0.82	0	0
2288	0.91	0	0
2289	0.32	1	1
2290	0.38	1	1
2291	0.33	1	1
2292	0.32	1	1
2293	0.54	0	0
2294	0.95	0	1
2295	0.79	0	0
2296	0.41	1	1
2297	0.21	1	1
2298	0.38	1	1
2299	0.40	1	1
2300	0.64	0	1
2301	0.69	0	1
2302	0.50	1	0
2303	0.58	0	1
2304	0.60	0	1
2305	0.51	0	1
2306	0.84	0	1
2307	0.76	0	1
2308	0.52	0	1
2309	0.70	0	1
2310	0.61	0	1
2311	0.64	0	1
2312	0.65	0	1
2313	0.53	0	1
2314	0.51	0	1
2315	0.63	0	1
2316	0.72	0	1
2317	0.61	0	1
2318	0.62	0	1
2319	0.61	0	1
2320	0.53	0	1
2321	0.65	0	1
2322	0.52	0	1
2323	0.70	0	1
2324	0.51	0	1
2325	0.51	0	1
2326	0.64	0	1
2327	0.69	0	1
2328	0.82	0	1
2329	0.80	0	1
2330	0.74	0	1
2331	0.77	0	1
2332	0.88	0	1
2333	0.68	0	1
2334	0.45	1	0
2335	0.58	0	1
2336	0.59	0	1
2337	0.66	0	1
2338	0.61	0	1
2339	0.63	0	1
2340	0.93	0	1
2341	0.44	1	0
2342	0.49	1	0
2343	0.62	0	1
2344	0.75	0	1
2345	0.50	1	0
2346	0.52	0	1
2347	0.54	0	1
2348	0.52	0	1
2349	0.64	0	1
2350	0.72	0	1
2351	0.58	0	1
2352	0.62	0	1
2353	0.56	0	1
2354	0.48	1	0
2355	0.54	0	1
2356	0.60	0	1
2357	0.60	0	1
2358	0.58	0	1
2359	0.49	1	0
2360	0.53	0	1
2361	0.45	1	0
2362	0.71	0	1
2363	0.66	0	1
2364	0.47	1	0
2365	0.50	0	1
2366	0.50	1	0
2367	0.81	0	1
2368	0.81	0	1
2369	0.53	0	1
2370	0.55	0	1
2371	0.53	0	1
2372	0.63	0	1
2373	0.81	0	1
2374	0.85	0	1
2375	0.55	0	1
2376	0.50	0	1
2377	0.50	0	1
2378	0.93	0	1
2379	0.95	0	1
2380	0.96	0	1
2381	0.75	0	1
2382	0.83	0	1
2383	0.78	0	1
2384	0.83	0	1
2385	0.81	0	1
2386	0.86	0	1
2387	0.87	0	1
2388	0.52	0	1
2389	0.46	1	0
2390	0.58	0	1
2391	0.78	0	1
2392	0.72	0	1
2393	0.49	1	0
2394	0.79	0	1
2395	0.49	1	0
2396	0.55	0	1
2397	0.50	0	1
2398	0.67	0	1
2399	0.82	0	1
2400	0.63	0	1
2401	0.83	0	1
2402	0.72	0	1
2403	0.89	0	1
2404	0.41	1	1
2405	0.33	1	1
2406	0.44	1	1
2407	0.43	1	1
2408	0.43	1	1
2409	0.85	0	0
2410	0.55	0	0
2411	0.32	1	1
2412	0.31	1	1
2413	0.43	1	1
2414	0.40	1	1
2415	0.53	0	0
2416	0.37	1	1
2417	0.26	1	1
2418	0.43	1	1
2419	0.32	1	1
2420	0.29	1	1
2421	0.37	1	1
2422	0.27	1	1
2423	0.34	1	1
2424	0.30	1	1
2425	0.63	0	0
2426	0.97	0	1
2427	0.49	1	0
2428	0.80	0	1
2429	0.74	0	1
2430	0.39	1	1
2431	0.70	0	0
2432	0.37	1	1
2433	0.32	1	1
2434	0.42	1	1
2435	0.61	0	1
2436	0.47	1	1
2437	0.85	0	1
2438	0.88	0	1
2439	0.80	0	1
2440	0.82	0	1
2441	0.85	0	1
2442	0.85	0	1
2443	0.82	0	1
2444	0.79	0	1
2445	0.88	0	1
2446	0.62	0	1
2447	0.79	0	1

2448	0.83	0	1
2449	0.63	0	1
2450	0.68	0	1
2451	0.98	0	1
2452	0.82	0	1
2453	0.86	0	1

2454	0.85	0	1
2455	0.86	0	1
2456	0.43	1	1
2457	0.39	1	1
2458	0.42	1	1
2459	0.63	0	0

2460	0.33	1	1
2461	0.28	1	1
2462	0.32	1	1
2463	0.39	1	1
2464	0.29	1	1
2465	0.31	1	1

2466	0.28	1	1
2467	0.26	1	1
2468	0.33	1	1
2469	0.32	1	1

APPENDIX C: TESTING RESULTS USING METHOD 3

Window size was 1000 sample points, the moving interval was 500 sample points, the total window number was 987. The detection criterion was: if $m_1 < 0$, set 'e' (Decision) = 0 (With DoS Attacks); if $\Delta m \leq m_{th}$, set 'e' (Decision) = 1 (No Attacks); if $\Delta m > m_{th}$, set 'e' (Decision) = 0 (With DoS Attacks). Test results are listed in the following table:

Column a: Window index number

Column b: m_1 (Slope of first half 500 sample points)

Column c: m_2 (Slope of second half 500 sample points)

Column d: Δm ($\Delta m = m_2 - m_1$)

Column e: Decision (1: No Attacks; 0 With DoS Attacks)

Column f: True/False (1: True; 0: False)

a	b	c	d	e	f
1	0.23	0.71	0.48	1	1
2	0.46	0.68	0.22	1	1
3	0.61	0.72	0.10	1	1
4	0.68	0.74	0.06	1	1
5	0.65	0.71	0.06	1	1
6	0.34	0.58	0.24	1	1
7	0.18	0.64	0.46	1	1
8	0.04	0.30	0.26	1	1
9	0.04	0.28	0.24	1	1
10	0.34	0.44	0.10	1	1
11	0.47	0.52	0.05	1	1
12	0.59	0.61	0.03	1	1
13	0.35	0.77	0.42	1	1
14	0.02	0.71	0.69	0	0
15	-0.01	0.94	0.95	0	1
16	0.28	0.74	0.46	1	0
17	0.20	0.99	0.78	0	1
18	0.31	0.72	0.42	1	0
19	-0.16	0.63	0.79	0	1
20	0.16	0.58	0.42	1	0
21	-0.06	1.05	1.11	0	1
22	-0.01	1.95	1.96	0	1
23	0.00	2.12	2.11	0	1
24	0.07	0.27	0.19	1	1
25	0.44	0.91	0.46	1	1
26	0.48	0.54	0.06	1	1
27	0.47	0.51	0.04	1	1
28	0.67	0.71	0.04	1	1
29	0.34	0.38	0.04	1	1
30	0.24	0.46	0.22	1	1
31	0.18	0.67	0.49	1	0
32	0.32	0.68	0.36	1	0
33	0.62	0.96	0.35	1	1
34	0.60	0.66	0.07	1	1
35	0.43	0.64	0.21	1	1
36	0.11	0.17	0.06	1	1
37	0.08	0.20	0.13	1	1
38	0.06	0.81	0.75	0	1
39	0.06	0.42	0.36	1	0
40	0.36	1.06	0.69	0	0
41	0.66	0.84	0.17	1	1
42	0.63	0.81	0.19	1	1
43	0.49	0.76	0.27	1	1
44	0.08	0.98	0.90	0	0
45	0.18	0.38	0.20	1	1
46	0.15	0.54	0.39	1	1
47	0.36	0.56	0.21	1	1
48	0.37	0.53	0.15	1	1
49	0.52	0.60	0.08	1	1
50	0.48	0.77	0.30	1	1

51	0.36	0.55	0.19	1	1
52	0.11	0.55	0.44	1	1
53	0.18	0.53	0.35	1	1
54	0.01	0.43	0.43	1	1
55	0.02	0.43	0.41	1	1
56	0.45	0.72	0.27	1	1
57	0.26	0.75	0.49	1	1
58	0.20	0.74	0.53	0	0
59	0.38	0.62	0.24	1	1
60	0.59	0.92	0.32	1	1
61	0.14	0.51	0.37	1	1
62	0.13	0.47	0.35	1	1
63	0.03	0.32	0.29	1	0
64	0.10	0.27	0.17	1	0
65	0.36	0.74	0.38	1	1
66	0.56	0.62	0.07	1	1
67	0.31	0.68	0.37	1	1
68	0.43	0.77	0.33	1	1
69	0.31	0.87	0.56	0	0
70	0.04	0.33	0.29	1	1
71	-0.11	0.23	0.35	0	0
72	0.01	0.30	0.30	1	1
73	0.19	0.31	0.11	1	1
74	0.72	0.91	0.20	1	1
75	0.45	0.50	0.04	1	1
76	0.27	0.47	0.20	1	1
77	0.24	0.60	0.37	1	1
78	0.49	0.52	0.04	1	1
79	0.20	0.77	0.57	0	1
80	0.06	0.74	0.68	0	1
81	0.00	0.23	0.23	0	1
82	0.00	0.48	0.48	1	0
83	0.03	0.38	0.35	1	1
84	0.01	0.68	0.67	0	0
85	0.00	0.70	0.70	0	0
86	0.00	2.12	2.12	0	1
87	0.06	1.69	1.63	0	1
88	-0.06	0.08	0.14	0	1
89	-0.04	0.05	0.09	0	1
90	-0.04	0.06	0.10	0	1
91	-0.11	0.80	0.91	0	1
92	-0.13	0.68	0.81	0	1
93	-0.05	0.06	0.11	0	1
94	-0.06	1.41	1.46	0	1
95	0.09	1.79	1.70	0	1
96	-0.08	1.29	1.37	0	1
97	-0.06	0.08	0.14	0	1
98	-0.05	0.06	0.11	0	1
99	-0.03	0.05	0.08	0	1
100	-0.04	0.06	0.10	0	1
101	0.01	1.97	1.97	0	1

102	0.00	1.68	1.69	0	1
103	0.01	0.23	0.22	1	0
104	0.02	0.77	0.75	0	1
105	0.00	0.94	0.93	0	0
106	-0.01	1.37	1.38	0	0
107	0.03	0.76	0.73	0	1
108	0.15	1.22	1.07	0	1
109	0.34	0.42	0.08	1	0
110	0.32	0.40	0.08	1	0
111	0.40	0.76	0.36	1	0
112	0.06	1.17	1.11	0	1
113	0.02	0.60	0.58	0	1
114	0.55	0.68	0.12	1	0
115	0.44	0.67	0.23	1	0
116	0.17	1.17	1.00	0	1
117	-0.01	0.77	0.78	0	1
118	0.26	0.73	0.47	1	0
119	0.37	0.47	0.10	1	0
120	0.24	0.76	0.53	0	1
121	0.09	0.49	0.40	1	0
122	0.04	0.86	0.82	0	1
123	0.47	0.49	0.02	1	0
124	0.36	0.38	0.03	1	0
125	0.08	1.11	1.04	0	1
126	0.08	0.90	0.81	0	1
127	0.28	0.82	0.54	0	1
128	0.44	0.49	0.05	1	0
129	0.27	0.73	0.47	1	0
130	0.09	1.03	0.94	0	1
131	0.45	0.46	0.01	1	0
132	0.04	0.49	0.44	1	0
133	0.28	0.50	0.23	1	0
134	0.15	0.27	0.11	1	0
135	0.23	0.26	0.04	1	0
136	-0.07	0.19	0.25	0	1
137	0.19	0.61	0.42	1	0
138	0.40	0.41	0.01	1	0
139	0.22	0.28	0.06	1	0
140	0.05	0.43	0.39	1	0
141	0.17	0.63	0.46	1	0
142	0.18	0.24	0.06	1	0
143	0.23	0.27	0.04	1	0
144	0.03	0.37	0.34	1	0
145	0.21	0.71	0.50	1	0
146	0.46	0.48	0.03	1	0
147	0.33	0.61	0.28	1	0
148	-0.04	1.00	1.04	0	1
149	0.01	0.21	0.20	1	0
150	0.48	0.56	0.08	1	1
151	0.09	0.21	0.12	1	1
152	0.50	0.59	0.08	1	0

153	0.00	0.41	0.41	1	0
154	0.00	0.43	0.43	1	1
155	0.19	0.65	0.45	1	1
156	0.16	1.00	0.84	0	1
157	0.10	0.31	0.21	1	0
158	0.10	0.34	0.24	1	0
159	0.56	0.67	0.11	1	1
160	0.50	0.83	0.33	1	1
161	0.48	0.53	0.05	1	1
162	0.35	0.68	0.32	1	1
163	0.31	0.40	0.09	1	1
164	0.27	0.67	0.40	1	1
165	0.07	0.92	0.85	0	1
166	0.15	0.65	0.50	0	1
167	0.04	0.27	0.23	1	1
168	0.24	0.38	0.13	1	1
169	0.43	0.56	0.12	1	1
170	0.37	0.47	0.10	1	1
171	0.26	0.48	0.22	1	1
172	0.25	0.71	0.46	1	1
173	0.03	1.16	1.13	0	1
174	0.05	1.15	1.10	0	1
175	0.25	0.88	0.63	0	0
176	0.18	0.37	0.19	1	1
177	0.47	0.64	0.18	1	1
178	0.47	0.53	0.06	1	1
179	0.37	0.65	0.28	1	1
180	0.15	0.53	0.38	1	1
181	0.15	0.56	0.41	1	1
182	0.15	0.41	0.26	1	1
183	-0.02	0.04	0.05	0	0
184	0.07	1.69	1.62	0	1
185	0.31	0.75	0.43	1	0
186	0.07	1.09	1.01	0	1
187	0.13	1.09	0.96	0	1
188	0.00	1.00	0.99	0	1
189	0.06	0.34	0.28	1	0
190	-0.04	0.42	0.46	0	1
191	-0.03	0.04	0.07	0	1
192	-0.02	0.31	0.33	0	1
193	0.19	0.38	0.18	1	0
194	0.01	0.12	0.11	1	0
195	0.05	0.36	0.31	1	0
196	0.12	1.08	0.96	0	1
197	0.09	2.35	2.26	0	1
198	0.00	2.13	2.13	0	1
199	-0.04	0.05	0.10	0	1
200	-0.04	0.05	0.09	0	1
201	-0.08	1.46	1.54	0	1
202	0.06	1.57	1.51	0	1
203	-0.06	0.07	0.13	0	1

204	-0.11	0.27	0.38	0	1
205	0.30	1.39	1.09	0	1
206	0.37	0.59	0.22	1	0
207	0.06	1.59	1.53	0	1
208	0.00	1.02	1.02	0	1
209	0.03	0.34	0.30	1	1
210	0.58	0.66	0.07	1	1
211	0.17	0.35	0.18	1	1
212	0.55	0.60	0.05	1	1
213	0.27	0.43	0.16	1	1
214	0.21	0.77	0.56	0	0
215	0.28	0.47	0.19	1	1
216	0.13	1.15	1.02	0	1
217	0.06	0.70	0.64	0	1
218	0.28	0.59	0.32	1	0
219	0.68	0.70	0.02	1	0
220	0.11	0.73	0.62	0	1
221	0.03	0.44	0.41	1	0
222	0.07	1.08	1.01	0	1
223	0.33	0.37	0.04	1	0
224	0.59	0.68	0.09	1	0
225	0.09	1.36	1.27	0	1
226	-0.05	0.44	0.48	0	1
227	0.21	0.83	0.62	0	1
228	0.37	0.70	0.34	1	0
229	0.11	0.33	0.22	1	0
230	0.00	0.24	0.24	0	1
231	0.13	1.25	1.12	0	1
232	0.30	0.33	0.03	1	0
233	0.56	0.73	0.16	1	0
234	0.12	1.29	1.17	0	1
235	-0.04	0.19	0.23	0	1
236	0.24	1.12	0.88	0	1
237	0.23	0.46	0.23	1	0
238	0.12	1.06	0.93	0	1
239	-0.05	0.23	0.28	0	1
240	0.58	0.60	0.01	1	0
241	0.12	0.31	0.19	1	0
242	0.14	0.65	0.51	0	1
243	0.16	0.37	0.22	1	0
244	0.15	0.29	0.14	1	0
245	-0.04	0.26	0.29	0	1
246	0.09	0.46	0.37	1	0
247	0.33	0.34	0.02	1	0
248	0.15	0.28	0.12	1	0
249	0.00	0.21	0.21	0	1
250	0.14	0.70	0.56	0	1
251	0.42	0.44	0.02	1	0
252	0.20	0.30	0.10	1	0
253	-0.02	0.33	0.34	0	1
254	0.01	0.23	0.22	1	0

255	0.36	0.71	0.35	1	0
256	0.32	0.83	0.51	0	1
257	0.04	1.73	1.69	0	1
258	0.54	1.09	0.55	0	1
259	0.33	0.61	0.28	1	0
260	0.63	1.06	0.43	1	0
261	0.17	0.32	0.15	1	0
262	0.03	0.95	0.92	0	1
263	0.07	0.21	0.14	1	0
264	-0.04	0.07	0.10	0	1
265	-0.04	0.05	0.09	0	1
266	-0.07	0.08	0.15	0	1
267	-0.05	0.06	0.11	0	1
268	-0.03	0.05	0.08	0	1
269	-0.06	0.08	0.14	0	1
270	-0.05	0.07	0.12	0	1
271	-0.04	0.05	0.09	0	1
272	-0.05	1.16	1.21	0	1
273	0.01	1.14	1.13	0	1
274	0.00	0.55	0.55	0	1
275	0.01	0.50	0.49	1	1
276	0.50	0.61	0.11	1	1
277	0.36	1.03	0.67	0	0
278	0.45	0.73	0.27	1	1
279	0.25	0.44	0.19	1	1
280	0.07	0.34	0.27	1	0
281	-0.01	0.22	0.23	0	1
282	0.00	1.89	1.89	0	0
283	0.00	1.22	1.22	0	1
284	-0.01	0.87	0.88	0	1
285	0.13	0.18	0.06	1	0
286	0.00	0.61	0.61	0	1
287	0.01	0.59	0.59	0	1
288	0.24	0.34	0.11	1	1
289	0.14	0.53	0.39	1	1
290	0.01	0.44	0.43	1	1
291	0.40	0.62	0.21	1	1
292	0.00	0.29	0.29	1	1
293	0.00	0.30	0.30	1	1
294	0.08	0.19	0.11	1	1
295	0.12	0.16	0.03	1	1
296	-0.02	0.24	0.26	0	0
297	0.00	0.32	0.32	1	1
298	0.00	0.35	0.35	0	1
299	0.01	1.54	1.54	0	1
300	0.36	1.56	1.20	0	1
301	0.14	0.60	0.45	1	0
302	-0.03	0.14	0.17	0	1
303	0.12	0.58	0.46	1	0
304	0.02	0.35	0.33	1	0
305	-0.07	0.10	0.17	0	1

306	0.01	0.35	0.34	1	0
307	0.04	0.54	0.50	0	1
308	0.02	0.47	0.45	1	0
309	0.00	0.59	0.59	0	1
310	-0.03	0.09	0.12	0	1
311	-0.02	0.03	0.05	0	1
312	-0.03	0.04	0.07	0	1
313	-0.04	0.06	0.10	0	1
314	0.02	0.84	0.82	0	1
315	0.11	0.63	0.53	0	1
316	0.05	0.22	0.18	1	0
317	-0.05	0.59	0.65	0	1
318	0.03	0.62	0.59	0	1
319	-0.04	0.05	0.09	0	1
320	-0.03	0.05	0.08	0	1
321	-0.03	0.04	0.07	0	1
322	-0.03	0.04	0.08	0	1
323	-0.03	0.04	0.08	0	1
324	-0.04	0.05	0.10	0	1
325	-0.03	0.04	0.08	0	1
326	0.02	0.22	0.21	1	0
327	-0.04	0.32	0.36	0	1
328	-0.03	0.05	0.08	0	1
329	-0.02	0.25	0.27	0	1
330	0.12	0.38	0.26	1	0
331	0.05	0.30	0.25	1	0
332	-0.03	0.64	0.68	0	1
333	-0.03	0.05	0.08	0	1
334	-0.04	0.05	0.09	0	1
335	-0.04	0.05	0.09	0	1
336	-0.04	1.41	1.45	0	1
337	0.11	0.88	0.76	0	1
338	-0.16	1.40	1.56	0	1
339	-0.06	0.07	0.13	0	1
340	-0.10	0.16	0.26	0	1
341	0.00	2.19	2.19	0	1
342	0.00	2.15	2.15	0	1
343	-0.04	0.05	0.09	0	1
344	-0.06	0.07	0.13	0	1
345	-0.04	0.05	0.09	0	1
346	-0.04	0.05	0.09	0	1
347	-0.08	0.11	0.18	0	1
348	0.11	1.66	1.55	0	1
349	-0.03	1.78	1.82	0	1
350	-0.11	0.16	0.27	0	1
351	-0.06	0.07	0.13	0	1
352	-0.05	0.07	0.13	0	1
353	-0.05	0.06	0.11	0	1
354	-0.09	0.23	0.32	0	1
355	-0.06	0.09	0.15	0	1
356	-0.03	0.04	0.08	0	1

357	-0.08	0.10	0.18	0	1
358	-0.05	0.06	0.10	0	1
359	-0.04	0.06	0.10	0	1
360	-0.06	0.08	0.14	0	1
361	-0.05	0.06	0.10	0	1
362	-0.11	0.26	0.37	0	1
363	-0.04	0.06	0.10	0	1
364	-0.07	0.11	0.18	0	1
365	-0.06	0.11	0.18	0	1
366	-0.07	0.09	0.16	0	1
367	-0.04	0.06	0.10	0	1
368	0.03	0.74	0.71	0	1
369	0.22	0.33	0.12	1	0
370	0.05	0.44	0.39	1	0
371	0.39	0.84	0.45	1	0
372	0.03	0.36	0.33	1	0
373	-0.05	0.27	0.33	0	1
374	0.02	0.19	0.18	1	0
375	0.00	0.15	0.15	1	0
376	0.04	0.61	0.57	0	1
377	0.24	0.83	0.59	0	1
378	0.04	0.34	0.30	1	0
379	0.03	0.07	0.04	1	0
380	-0.07	0.17	0.25	0	1
381	0.03	0.06	0.02	1	0
382	-0.10	0.26	0.36	0	1
383	0.03	0.11	0.08	1	0
384	-0.01	0.03	0.04	0	1
385	-0.02	0.07	0.08	0	1
386	-0.05	0.09	0.14	0	1
387	-0.04	0.06	0.10	0	1
388	-0.03	0.04	0.07	0	1
389	-0.03	0.05	0.08	0	1
390	-0.04	0.05	0.09	0	1
391	-0.03	0.04	0.07	0	1
392	-0.04	0.05	0.09	0	1
393	-0.04	0.05	0.09	0	1
394	-0.03	0.04	0.08	0	1
395	-0.04	0.05	0.09	0	1
396	-0.03	0.05	0.08	0	1
397	-0.04	0.05	0.09	0	1
398	-0.03	0.04	0.07	0	1
399	-0.03	0.04	0.08	0	1
400	-0.03	0.04	0.07	0	1
401	-0.05	0.07	0.12	0	1
402	-0.03	0.04	0.08	0	1
403	-0.03	0.04	0.07	0	1
404	-0.04	0.05	0.09	0	1
405	-0.03	0.05	0.08	0	1
406	-0.03	0.05	0.08	0	1
407	-0.03	0.05	0.08	0	1

408	-0.03	0.05	0.08	0	1
409	-0.03	0.04	0.07	0	1
410	-0.03	0.05	0.08	0	1
411	-0.03	0.05	0.08	0	1
412	-0.03	0.04	0.07	0	1
413	-0.03	0.05	0.08	0	1
414	-0.03	0.05	0.08	0	1
415	-0.05	0.07	0.12	0	1
416	-0.04	0.05	0.10	0	1
417	-0.04	0.05	0.08	0	1
418	-0.04	0.05	0.10	0	1
419	-0.03	0.05	0.08	0	1
420	-0.03	0.04	0.07	0	1
421	-0.03	0.04	0.07	0	1
422	-0.03	0.05	0.08	0	1
423	-0.03	0.04	0.07	0	1
424	-0.04	0.05	0.09	0	1
425	-0.04	0.05	0.09	0	1
426	-0.04	0.06	0.09	0	1
427	-0.03	0.05	0.08	0	1
428	-0.03	0.05	0.08	0	1
429	-0.03	0.05	0.08	0	1
430	-0.03	0.04	0.08	0	1
431	-0.03	0.04	0.07	0	1
432	-0.03	0.05	0.08	0	1
433	-0.03	0.05	0.08	0	1
434	-0.03	0.04	0.07	0	1
435	-0.03	0.04	0.07	0	1
436	-0.04	0.05	0.09	0	1
437	-0.04	0.05	0.09	0	1
438	-0.03	0.04	0.07	0	1
439	-0.03	0.04	0.07	0	1
440	-0.03	0.04	0.08	0	1
441	-0.03	0.05	0.08	0	1
442	-0.04	0.06	0.10	0	1
443	-0.04	0.05	0.09	0	1
444	-0.03	0.05	0.08	0	1
445	-0.03	0.04	0.07	0	1
446	-0.04	0.05	0.08	0	1
447	-0.03	0.05	0.08	0	1
448	-0.03	0.05	0.08	0	1
449	-0.04	0.05	0.09	0	1
450	-0.03	0.05	0.08	0	1
451	-0.04	0.05	0.09	0	1
452	-0.04	0.05	0.09	0	1
453	-0.04	0.06	0.10	0	1
454	-0.03	0.04	0.07	0	1
455	-0.05	0.06	0.11	0	1
456	-0.04	0.05	0.09	0	1
457	-0.03	0.04	0.07	0	1
458	-0.03	0.04	0.08	0	1
459	-0.03	0.04	0.07	0	1
460	-0.03	0.05	0.08	0	1
461	-0.03	0.04	0.07	0	1
462	-0.03	0.04	0.08	0	1
463	-0.03	0.04	0.07	0	1
464	-0.03	0.05	0.08	0	1
465	-0.03	0.04	0.08	0	1
466	-0.03	0.04	0.07	0	1
467	-0.03	0.05	0.08	0	1
468	-0.05	0.06	0.10	0	1
469	-0.04	0.05	0.08	0	1
470	-0.03	0.05	0.08	0	1
471	-0.03	0.04	0.07	0	1
472	-0.03	0.04	0.07	0	1
473	-0.03	0.05	0.08	0	1
474	-0.03	0.04	0.07	0	1
475	-0.03	0.04	0.07	0	1
476	-0.03	0.04	0.07	0	1
477	-0.03	0.05	0.08	0	1
478	-0.03	0.05	0.08	0	1
479	-0.03	0.04	0.08	0	1
480	-0.03	0.04	0.07	0	1
481	-0.03	0.05	0.08	0	1
482	-0.03	0.05	0.08	0	1
483	-0.04	0.05	0.09	0	1
484	-0.03	0.05	0.08	0	1
485	-0.04	0.05	0.09	0	1
486	-0.04	0.06	0.10	0	1
487	-0.03	0.04	0.07	0	1
488	-0.05	0.06	0.11	0	1
489	-0.03	0.05	0.08	0	1
490	-0.03	0.04	0.07	0	1
491	-0.03	0.05	0.08	0	1
492	-0.04	0.05	0.08	0	1
493	-0.04	0.05	0.10	0	1
494	-0.04	0.05	0.09	0	1
495	-0.03	0.04	0.08	0	1
496	-0.04	0.05	0.09	0	1
497	-0.03	0.05	0.08	0	1
498	-0.03	0.04	0.08	0	1
499	-0.04	0.05	0.08	0	1
500	-0.03	0.05	0.08	0	1
501	-0.03	0.05	0.08	0	1
502	-0.04	0.06	0.10	0	1
503	-0.04	0.05	0.09	0	1
504	-0.04	0.05	0.08	0	1
505	-0.03	0.05	0.08	0	1
506	-0.03	0.04	0.07	0	1
507	-0.03	0.05	0.08	0	1
508	-0.03	0.04	0.07	0	1
509	-0.04	0.05	0.09	0	1

510	-0.04	0.05	0.10	0	1
511	-0.03	0.04	0.08	0	1
512	-0.04	0.05	0.08	0	1
513	-0.03	0.05	0.08	0	1
514	-0.04	0.05	0.09	0	1
515	-0.03	0.04	0.07	0	1
516	-0.05	0.06	0.11	0	1
517	-0.03	0.04	0.07	0	1
518	-0.03	0.04	0.07	0	1
519	-0.04	0.05	0.09	0	1
520	-0.03	0.05	0.08	0	1
521	-0.04	0.05	0.09	0	1
522	-0.03	0.04	0.07	0	1
523	-0.04	0.05	0.08	0	1
524	-0.04	0.05	0.09	0	1
525	-0.04	0.05	0.09	0	1
526	-0.04	0.06	0.10	0	1
527	-0.03	0.04	0.07	0	1
528	-0.03	0.04	0.07	0	1
529	-0.05	0.06	0.11	0	1
530	-0.04	0.06	0.09	0	1
531	-0.05	0.06	0.11	0	1
532	-0.04	0.05	0.10	0	1
533	-0.03	0.04	0.07	0	1
534	-0.04	0.05	0.08	0	1
535	-0.05	0.06	0.11	0	1
536	-0.03	0.05	0.08	0	1
537	-0.04	0.05	0.09	0	1
538	-0.03	0.04	0.08	0	1
539	-0.03	0.05	0.08	0	1
540	-0.04	0.06	0.10	0	1
541	-0.04	0.05	0.09	0	1
542	-0.04	0.06	0.10	0	1
543	-0.04	0.06	0.10	0	1
544	-0.04	0.05	0.09	0	1
545	-0.03	0.05	0.08	0	1
546	-0.04	0.05	0.09	0	1
547	-0.04	0.05	0.09	0	1
548	-0.03	0.05	0.08	0	1
549	-0.04	0.05	0.09	0	1
550	-0.05	0.06	0.11	0	1
551	-0.04	0.05	0.09	0	1
552	-0.03	0.04	0.08	0	1
553	-0.03	0.05	0.08	0	1
554	-0.03	0.05	0.08	0	1
555	-0.07	0.12	0.19	0	1
556	-0.06	0.10	0.16	0	1
557	-0.03	0.04	0.07	0	1
558	-0.05	0.06	0.10	0	1
559	-0.07	0.09	0.17	0	1
560	-0.04	0.06	0.10	0	1

561	-0.04	0.05	0.09	0	1
562	-0.03	0.04	0.08	0	1
563	-0.04	0.05	0.09	0	1
564	-0.04	0.05	0.09	0	1
565	-0.03	0.05	0.09	0	1
566	-0.04	0.05	0.09	0	1
567	-0.04	0.05	0.09	0	1
568	-0.04	0.05	0.09	0	1
569	-0.04	0.06	0.10	0	1
570	-0.03	0.05	0.08	0	1
571	-0.03	0.05	0.08	0	1
572	-0.05	0.06	0.10	0	1
573	-0.04	0.05	0.09	0	1
574	-0.04	0.05	0.09	0	1
575	-0.04	0.06	0.10	0	1
576	-0.04	0.06	0.10	0	1
577	-0.03	0.05	0.08	0	1
578	-0.04	0.05	0.09	0	1
579	-0.05	0.07	0.12	0	1
580	-0.04	0.06	0.10	0	1
581	-0.04	0.05	0.08	0	1
582	-0.03	0.04	0.08	0	1
583	-0.04	0.05	0.10	0	1
584	-0.04	0.05	0.08	0	1
585	-0.05	0.07	0.12	0	1
586	-0.20	0.59	0.79	0	1
587	-0.07	0.14	0.21	0	1
588	-0.06	0.08	0.14	0	1
589	-0.04	0.06	0.10	0	1
590	-0.04	0.05	0.09	0	1
591	-0.04	0.05	0.09	0	1
592	-0.04	0.06	0.10	0	1
593	-0.04	0.05	0.09	0	1
594	-0.10	0.12	0.22	0	1
595	-0.03	0.04	0.07	0	1
596	-0.03	0.05	0.08	0	1
597	-0.06	0.08	0.13	0	1
598	-0.03	0.05	0.08	0	1
599	-0.04	0.05	0.09	0	1
600	-0.08	0.13	0.20	0	1
601	-0.04	0.05	0.09	0	1
602	-0.03	0.05	0.08	0	1
603	-0.04	0.05	0.09	0	1
604	-0.06	0.07	0.13	0	1
605	-0.08	0.15	0.23	0	1
606	-0.06	0.07	0.13	0	1
607	-0.07	0.11	0.18	0	1
608	-0.05	0.07	0.12	0	1
609	-0.03	0.05	0.08	0	1
610	-0.03	0.05	0.08	0	1
611	-0.03	0.05	0.08	0	1

612	-0.04	0.06	0.10	0	1
613	-0.04	0.05	0.09	0	1
614	-0.04	0.05	0.09	0	1
615	-0.04	0.05	0.09	0	1
616	-0.10	0.57	0.67	0	1
617	-0.06	0.09	0.15	0	1
618	-0.04	0.05	0.09	0	1
619	-0.05	0.07	0.12	0	1
620	-0.05	0.06	0.10	0	1
621	-0.04	0.05	0.09	0	1
622	-0.04	0.06	0.10	0	1
623	-0.05	0.07	0.12	0	1
624	-0.04	0.05	0.09	0	1
625	-0.04	0.05	0.09	0	1
626	-0.04	0.05	0.08	0	1
627	-0.05	0.06	0.10	0	1
628	-0.04	0.05	0.09	0	1
629	-0.04	0.05	0.09	0	1
630	-0.05	0.07	0.12	0	1
631	-0.05	0.06	0.10	0	1
632	-0.07	0.09	0.15	0	1
633	-0.04	0.05	0.08	0	1
634	-0.04	0.05	0.09	0	1
635	-0.04	0.05	0.09	0	1
636	-0.05	0.07	0.12	0	1
637	-0.06	0.09	0.15	0	1
638	-0.03	0.05	0.08	0	1
639	-0.04	0.05	0.09	0	1
640	-0.03	0.04	0.08	0	1
641	-0.04	0.05	0.09	0	1
642	-0.04	0.05	0.08	0	1
643	-0.04	0.05	0.09	0	1
644	-0.04	0.05	0.08	0	1
645	-0.04	0.05	0.09	0	1
646	-0.07	0.13	0.19	0	1
647	-0.04	0.06	0.10	0	1
648	-0.04	0.06	0.10	0	1
649	-0.05	0.06	0.11	0	1
650	-0.04	0.05	0.09	0	1
651	-0.04	0.05	0.09	0	1
652	-0.06	0.08	0.13	0	1
653	-0.06	0.09	0.16	0	1
654	-0.04	0.05	0.09	0	1
655	-0.07	0.08	0.15	0	1
656	-0.03	0.05	0.08	0	1
657	-0.13	0.27	0.40	0	1
658	-0.05	0.07	0.12	0	1
659	-0.04	0.05	0.09	0	1
660	-0.09	0.20	0.29	0	1
661	-0.05	0.06	0.11	0	1
662	-0.05	0.07	0.12	0	1

663	-0.04	0.05	0.09	0	1
664	-0.05	0.07	0.12	0	1
665	-0.12	0.17	0.29	0	1
666	-0.03	0.05	0.08	0	1
667	-0.04	0.06	0.10	0	1
668	-0.04	0.06	0.10	0	1
669	-0.04	0.05	0.09	0	1
670	-0.19	0.43	0.62	0	1
671	-0.05	0.07	0.12	0	1
672	-0.09	0.16	0.25	0	1
673	-0.10	0.16	0.26	0	1
674	-0.08	0.12	0.21	0	1
675	-0.10	0.14	0.24	0	1
676	-0.07	0.09	0.17	0	1
677	-0.14	0.48	0.62	0	1
678	-0.11	0.33	0.45	0	1
679	-0.10	0.21	0.31	0	1
680	-0.09	0.14	0.23	0	1
681	-0.04	0.05	0.09	0	1
682	-0.07	0.11	0.17	0	1
683	-0.03	0.04	0.07	0	1
684	-0.08	0.12	0.20	0	1
685	-0.06	1.13	1.19	0	1
686	0.01	0.99	0.98	0	1
687	0.03	0.70	0.68	0	0
688	0.36	0.47	0.11	1	1
689	0.40	0.55	0.14	1	0
690	0.02	0.39	0.37	1	0
691	0.02	0.38	0.36	1	0
692	0.36	0.43	0.07	1	0
693	0.05	1.17	1.12	0	1
694	0.00	1.23	1.22	0	1
695	0.00	0.39	0.39	1	1
696	0.00	0.38	0.38	1	1
697	-0.08	0.64	0.72	0	0
698	0.12	0.83	0.71	0	1
699	0.11	0.27	0.17	1	0
700	0.10	0.87	0.77	0	1
701	0.44	0.54	0.10	1	0
702	0.49	0.78	0.29	1	0
703	0.02	0.71	0.69	0	1
704	-0.01	0.26	0.27	0	1
705	0.23	0.54	0.30	1	0
706	0.48	0.50	0.02	1	0
707	0.04	0.46	0.42	1	0
708	0.18	0.30	0.12	1	0
709	0.12	0.99	0.87	0	1
710	0.55	0.56	0.01	1	0
711	0.39	0.50	0.11	1	0
712	0.08	1.12	1.04	0	1
713	0.04	1.10	1.06	0	1

714	0.42	0.69	0.26	1	0
715	0.54	0.59	0.06	1	0
716	0.13	0.61	0.47	1	0
717	-0.01	0.11	0.13	0	1
718	0.02	0.78	0.76	0	1
719	0.58	0.71	0.13	1	0
720	0.51	0.62	0.11	1	0
721	0.10	1.05	0.95	0	1
722	0.35	0.38	0.03	1	0
723	0.13	0.38	0.25	1	0
724	0.08	0.42	0.34	1	0
725	0.24	0.47	0.23	1	0
726	0.19	0.27	0.08	1	0
727	0.15	0.51	0.37	1	0
728	0.12	0.53	0.41	1	0
729	0.47	0.50	0.02	1	0
730	0.48	0.55	0.07	1	0
731	0.29	0.89	0.60	0	1
732	0.10	0.48	0.38	1	0
733	0.62	0.71	0.08	1	0
734	0.36	0.58	0.21	1	0
735	0.08	0.76	0.68	0	1
736	0.01	0.85	0.84	0	1
737	0.36	0.79	0.43	1	0
738	0.20	0.27	0.07	1	0
739	0.24	0.71	0.46	1	0
740	0.00	0.48	0.48	1	0
741	0.04	0.63	0.59	0	1
742	-0.07	0.65	0.72	0	1
743	-0.01	0.08	0.08	0	1
744	-0.04	0.39	0.43	0	1
745	0.13	0.18	0.05	1	0
746	0.16	0.23	0.07	1	0
747	0.11	0.42	0.31	1	0
748	0.01	0.21	0.19	1	0
749	0.16	0.27	0.10	1	0
750	0.21	0.26	0.05	1	0
751	0.39	0.42	0.03	1	0
752	0.17	0.41	0.24	1	0
753	-0.02	0.23	0.24	0	1
754	0.19	0.27	0.08	1	0
755	0.10	0.19	0.09	1	0
756	0.19	0.24	0.05	1	0
757	0.20	0.32	0.12	1	0
758	0.03	0.33	0.30	1	0
759	0.42	0.43	0.01	1	0
760	0.14	0.25	0.12	1	0
761	0.20	0.29	0.08	1	0
762	0.05	0.38	0.33	1	0
763	0.41	0.57	0.16	1	0
764	0.59	0.60	0.01	1	0

765	0.26	0.43	0.17	1	0
766	0.17	0.64	0.46	1	0
767	0.45	0.46	0.01	1	0
768	0.23	0.27	0.04	1	0
769	0.14	0.25	0.11	1	0
770	-0.03	0.16	0.19	0	1
771	0.09	0.27	0.18	1	0
772	0.15	0.25	0.10	1	0
773	0.24	0.28	0.04	1	0
774	0.23	0.56	0.33	1	0
775	0.46	0.59	0.13	1	0
776	-0.02	0.49	0.51	0	1
777	0.34	0.37	0.03	1	0
778	0.37	0.42	0.05	1	0
779	0.60	0.61	0.02	1	0
780	0.43	0.46	0.04	1	0
781	0.26	0.71	0.45	1	0
782	0.31	0.38	0.07	1	0
783	0.16	0.25	0.09	1	0
784	0.09	0.21	0.12	1	0
785	0.24	0.28	0.04	1	0
786	0.07	0.48	0.42	1	0
787	0.33	0.38	0.04	1	0
788	0.23	0.28	0.05	1	0
789	0.08	0.21	0.12	1	0
790	0.25	0.28	0.03	1	0
791	0.00	0.33	0.34	0	1
792	0.35	0.45	0.10	1	0
793	0.15	0.39	0.24	1	0
794	-0.01	0.38	0.39	0	1
795	0.09	0.29	0.20	1	0
796	0.05	0.15	0.10	1	0
797	-0.05	0.16	0.22	0	1
798	0.03	0.07	0.04	1	0
799	-0.03	0.33	0.37	0	1
800	0.01	0.35	0.34	1	0
801	-0.01	0.11	0.12	0	1
802	-0.03	0.08	0.11	0	1
803	0.03	0.06	0.02	1	0
804	-0.12	0.17	0.29	0	1
805	0.01	0.05	0.04	1	0
806	0.01	0.16	0.14	1	0
807	0.02	0.12	0.10	1	0
808	-0.07	0.17	0.24	0	1
809	0.00	0.03	0.03	1	0
810	-0.01	0.06	0.07	0	1
811	-0.06	0.10	0.15	0	1
812	-0.01	0.04	0.05	0	1
813	-0.04	0.05	0.09	0	1
814	-0.02	0.05	0.08	0	1
815	-0.03	0.06	0.09	0	1

816	-0.03	0.05	0.08	0	1
817	-0.02	0.04	0.07	0	1
818	-0.04	0.06	0.11	0	1
819	-0.02	0.04	0.06	0	1
820	-0.03	0.06	0.09	0	1
821	-0.03	0.05	0.08	0	1
822	-0.05	0.07	0.12	0	1
823	-0.03	0.05	0.08	0	1
824	-0.03	0.05	0.08	0	1
825	-0.04	0.05	0.09	0	1
826	-0.03	0.05	0.08	0	1
827	-0.03	0.05	0.08	0	1
828	-0.03	0.05	0.08	0	1
829	-0.04	0.06	0.10	0	1
830	-0.02	0.06	0.08	0	1
831	-0.03	0.06	0.09	0	1
832	-0.01	0.05	0.06	0	1
833	-0.02	0.05	0.08	0	1
834	0.00	0.06	0.06	0	1
835	-0.04	0.06	0.11	0	1
836	-0.05	0.09	0.14	0	1
837	-0.01	0.05	0.06	0	1
838	-0.04	0.08	0.12	0	1
839	-0.02	0.05	0.08	0	1
840	-0.05	0.07	0.11	0	1
841	0.02	0.06	0.05	1	0
842	-0.01	0.10	0.10	0	1
843	-0.04	0.12	0.16	0	1
844	-0.01	0.04	0.06	0	1
845	-0.08	0.14	0.22	0	1
846	-0.01	0.04	0.05	0	1
847	-0.10	0.16	0.26	0	1
848	0.00	0.10	0.10	0	1
849	-0.06	0.17	0.23	0	1
850	-0.04	0.05	0.09	0	1
851	-0.06	0.09	0.16	0	1
852	-0.07	0.09	0.15	0	1
853	-0.05	0.09	0.13	0	1
854	-0.08	0.19	0.27	0	1
855	-0.05	0.06	0.11	0	1
856	-0.04	0.05	0.10	0	1
857	-0.08	0.27	0.36	0	1
858	-0.05	0.09	0.14	0	1
859	-0.01	0.11	0.13	0	1
860	-0.07	0.20	0.26	0	1
861	-0.01	0.06	0.07	0	1
862	-0.04	0.11	0.15	0	1
863	-0.11	0.19	0.30	0	1
864	-0.03	0.07	0.10	0	1
865	-0.03	0.16	0.19	0	1
866	-0.01	0.09	0.10	0	1

867	-0.04	0.12	0.16	0	1
868	-0.05	0.12	0.17	0	1
869	-0.03	0.05	0.08	0	1
870	-0.06	0.09	0.15	0	1
871	-0.02	0.04	0.06	0	1
872	-0.15	0.24	0.39	0	1
873	-0.08	0.12	0.19	0	1
874	0.08	0.94	0.86	0	1
875	-0.01	0.07	0.07	0	1
876	0.03	0.28	0.25	1	0
877	-0.02	0.05	0.07	0	1
878	-0.07	0.16	0.23	0	1
879	0.01	0.04	0.03	1	0
880	-0.04	0.06	0.11	0	1
881	-0.04	0.06	0.10	0	1
882	-0.09	0.28	0.37	0	1
883	-0.05	0.06	0.11	0	1
884	-0.03	0.05	0.08	0	1
885	-0.05	0.06	0.11	0	1
886	-0.05	0.06	0.11	0	1
887	-0.11	0.23	0.35	0	1
888	-0.07	0.11	0.18	0	1
889	-0.08	0.11	0.19	0	1
890	-0.10	0.19	0.29	0	1
891	-0.04	0.10	0.14	0	1
892	-0.10	0.33	0.43	0	1
893	-0.11	0.22	0.33	0	1
894	-0.12	0.39	0.51	0	1
895	0.08	0.15	0.07	1	0
896	-0.05	0.17	0.22	0	1
897	-0.13	0.24	0.36	0	1
898	-0.04	0.05	0.09	0	1
899	0.00	1.35	1.35	0	1
900	0.00	1.34	1.35	0	1
901	0.00	0.38	0.38	1	1
902	0.00	0.39	0.39	1	1
903	0.11	0.61	0.50	1	1
904	0.02	0.38	0.37	1	0
905	0.00	0.40	0.40	1	0
906	0.06	0.72	0.66	0	0
907	0.00	0.36	0.36	1	1
908	0.00	0.36	0.36	1	1
909	0.11	0.28	0.17	1	1
910	0.08	0.89	0.81	0	0
911	0.53	0.59	0.06	1	0
912	0.34	0.44	0.10	1	0
913	0.05	0.77	0.72	0	1
914	0.00	0.37	0.37	1	1
915	0.00	0.37	0.37	1	1
916	0.16	0.48	0.31	1	1
917	0.00	0.58	0.58	0	1

918	0.00	0.65	0.65	0	1
919	0.01	0.62	0.61	0	1
920	0.20	0.54	0.34	1	0
921	0.08	1.24	1.16	0	1
922	0.43	0.81	0.38	1	0
923	0.52	0.60	0.08	1	0
924	0.06	1.07	1.01	0	1
925	0.12	0.69	0.57	0	1
926	0.08	1.00	0.92	0	1
927	0.17	0.73	0.56	0	1
928	0.35	0.57	0.22	1	0
929	0.09	1.16	1.06	0	1
930	0.08	1.05	0.97	0	1
931	0.17	0.19	0.03	1	0
932	0.34	0.53	0.19	1	0
933	0.09	0.49	0.41	1	0
934	-0.05	0.18	0.24	0	1
935	0.14	1.18	1.05	0	1
936	0.22	0.56	0.34	1	0
937	0.34	0.90	0.57	0	1
938	-0.03	0.34	0.38	0	1
939	0.02	0.22	0.20	1	0
940	0.13	1.20	1.07	0	1
941	0.25	0.90	0.65	0	1
942	0.01	0.73	0.72	0	1
943	0.25	0.40	0.15	1	0
944	0.29	0.38	0.09	1	0
945	0.10	0.52	0.42	1	0
946	0.39	0.49	0.09	1	0
947	0.22	0.25	0.03	1	0
948	0.20	0.28	0.08	1	0
949	-0.13	0.30	0.43	0	1
950	0.07	0.22	0.15	1	0
951	0.16	0.27	0.10	1	0
952	0.12	0.38	0.25	1	0

953	-0.08	0.15	0.23	0	1
954	0.08	0.32	0.24	1	0
955	0.07	0.20	0.13	1	0
956	0.11	0.29	0.18	1	0
957	-0.02	0.22	0.24	0	1
958	0.05	0.28	0.23	1	0
959	0.11	0.23	0.12	1	0
960	0.30	0.59	0.29	1	0
961	-0.04	0.28	0.32	0	1
962	0.20	0.48	0.27	1	0
963	0.00	0.30	0.30	1	1
964	0.00	0.31	0.30	1	1
965	0.08	0.86	0.78	0	0
966	0.20	0.84	0.64	0	0
967	0.53	0.83	0.30	1	1
968	0.36	0.88	0.52	0	0
969	0.18	0.39	0.20	1	1
970	-0.03	0.30	0.33	0	1
971	0.28	0.68	0.40	1	0
972	0.01	0.98	0.97	0	1
973	0.22	0.91	0.68	0	1
974	-0.02	0.04	0.06	0	1
975	-0.02	0.04	0.06	0	1
976	-0.03	0.05	0.08	0	1
977	-0.07	0.09	0.15	0	1
978	-0.06	0.07	0.13	0	1
979	-0.08	0.10	0.18	0	1
980	-0.06	0.07	0.13	0	1
981	-0.07	0.64	0.70	0	1
982	0.01	0.57	0.55	0	1
983	0.06	0.49	0.43	1	1
984	0.18	0.51	0.33	1	1
985	0.35	0.49	0.15	1	1
986	0.50	0.55	0.04	1	1
987	0.35	0.56	0.21	1	1