



MTA -GSM channel model for wireless communication

J.Lakshmi Narayanan, J.Arunachalam, S.Subashini

ijnjaya007@gmail.com; arun.kaashiv@gmail.com; suba.venkat@yahoo.com

Kaashiv InfoTech, Chennai-600040.

Abstract:

Network simulator is the technique that predicts the behaviour of network and this simulation is observed by tracing of network. These tracing also divided into two categories: Consistence and Non-consistence. Several algorithms had proposed already but almost of them have inconsistence level of traces. Consistence traces produce the more approximate result for prediction. Here we compare two effective algorithms that are GSM & MTA model based traces. We use GSM traces in GSM model and generate error containing subtraces by MTA algorithm. Then we applied these traces in burst length and in run test. On these observations we proof the consistency of MTA algorithm. Also we differentiate these terms in graphical form. Keywords: Graph, error statistics, Table Introduction

For these comparison, MTA algorithm generate a statistical constant.[4] Apply these constant to identify error containing and errorless segments of transmission. By analyzing the length distributions graph of the error containing and errorless segments, we can effectively characterize the transitions between them. So that it can be applied to wireless traces which analyze different error Statistics over time. Then compare with artificial traces using the MTA and Markov GSM models. [7] In next section, we discuss background information about Discrete Time Markov Chains. Then describe MTA algorithm and proof MTA algorithm have more consistency them GSM traces. [6] Background In this section, we describe for Discrete Time Markov Chains (DTMC) and related properties. Discrete time Markov chains A Discrete Time Markov Chain (DTMC) [3] is a random process that takes values in a discrete places P . A DTMC is defined by its memory and its transition probabilities of Q steps, where Q defines the memory. To calculate the memory of a DTMC we introduce the concept of situational entropy. The situational entropy is an indication of the randomness of the next element of a trace. We determine the amount of past history necessary by calculating the initial order entropy l range of l varies from 1 to U . We choose U to be 7 because maintaining history for 27 or 128 states produces a reasonable level of implementation and processing complexity (more states lead to calculated).

ENTROPY FOR The ERRORNESS SUBTRACE

The MTA algorithm: The basic concept of the MTA algorithm that an error traces with non-consistence behaviour can be decomposed into a consistence subset that consisting of error containing states. The MTA algorithm defines two states, the error containing and the errorless

states and parameterize transitions between them for preset the parameters, varying the state constant. Errorless states contain only correctly transmitted frames, while error containing states consists of both and error frames as well as errorless frames. We show that exhibit consistency by error containing states in its error statistics, So that they can be modelled with a traditional DTMC. The MTA algorithm



computes the lengths distribution for both errorless and error containing states, along with the memory and parameters used on the sequence of error containing states in DTMC.

In this section, we first discuss consistency properties then show how to trace for consistency. Then we present the MTA algorithm and show how it is applied for tracing

Consistency

We consider a random process $\{E_n \mid n \geq 0\}$ with a discrete space $M = \{0, 1\}$ for network traffic trace, whereas, „0“ indicates a correct transmit frame and „1“ indicates a corrupted frame. A process E_n that takes values on the discrete space $M = \{0, 1\}$ is also called a binary time series [6].

We define a trace to be consistency whenever the error statistics remain constant over time on given window size for examine. In comparison the length of errorless bursts are significantly longer than the length of error bursts [5].

Order (Q)	entropy
7	0.5194
6	0.5208
5	0.5213
4	0.5224
3	0.5254
2	0.5364
1	0.5476

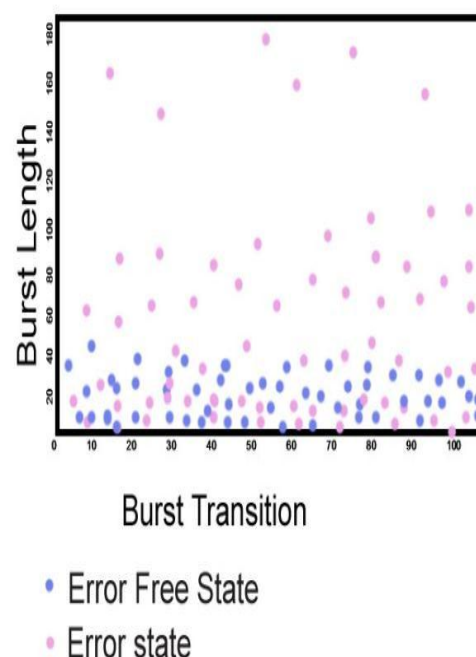


Figure 1. Burst length in GSM trace.



We identify trace sections that exhibit consistence properties by finding errorless bursts of length equal to or greater than the change-of-state constant S . The value of S is key point that defines as to sum of mean and standard deviation of the length of error bursts of a trace. If we remove trace sections consisting of errorless bursts of length equal to or greater than S , significantly we can say that the resulting trace will have consistency error statistic properties. We use the test for consistency [7], summarized as follows:

1. Define a run as a number of consecutive ones.
2. Divide the trace into equal length parts.
3. Compute the lengths of runs in each part.
4. Count the number of runs(error burst) of length above and below
5. For a consistence trace, the number of runs distribution between

the 0.06 and 0.94 cut-offs will be eliminate up to 90% approximate [7].

6. Plot a histogram for the number of runs.

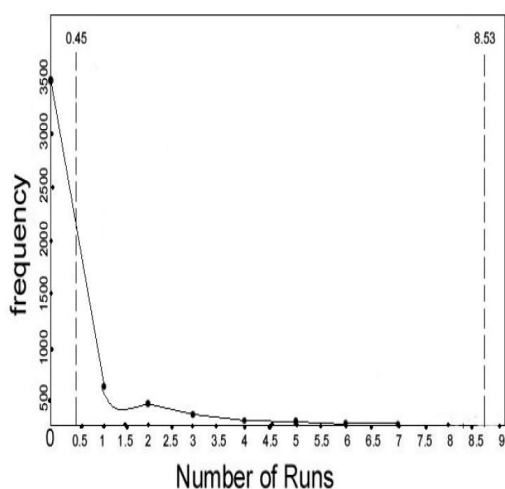


Figure 2. The run test applied to GSM trace

We apply the Run Test to test GSM trace for check consistency. First we compute the mean and standard deviation for the error burst length. Here, the mean value was found to be 7 frames and the standard deviation was 13 frames, producing a state-of-change constant value S of 20 ($7 + 13$) frames. The average error cluster size was found to be 22 frames and the standard deviation was 56 frames. We take the window size for the Runs Test to be 55.

Figure 2 shows that only 17% of the runs distribution lie between the ranges 0.06 and 0.94, and 83.4% lies outside the both left and right cut offs. Thus, from the Runs Test, we conclude that GSM trace exerts a non-consistence process for a window size of 55. Algorithm: The MTA algorithm considers two types of states to trace a process: error containing and errorless. The algorithm extracts error containing states from the error trace and concatenates these states to form error containing subtrace. We define two random processes with a discrete space $M = \{0, 1, 2, \dots\}$.

- The error containing state length process $\{A_n \mid n \geq 0\}$, where A_n represents the number of elements in the n th error containing state(i.e., length of state)
- The errorless state length process $\{T_n \mid n \geq 0\}$, where T_n represents the length of the n th errorless state.

The distributions of A_n and T_n are found by introducing the cumulative density function (CDF) and finding the “best” fitting distributions. The error containing subtrace is a consistence random process; therefore, it can be modelled as a DTMC with a certain memory. The MTA algorithm calculates the memory of the error containing sub-traces and finds its transition probabilities. The application of the



MTA algorithm to an input trace can be summarized as follows:

1. Calculate the mean (m) and standard deviation (sd) values

for error burst lengths in the trace.

2. Set value of constant S (change-of-state constant), equal to $(m + sd)$.

3. Decompose the trace into error containing state and errorless state portions using the following integrity:

Errorless state: runs of 0's that have length $> S$.

4. Create error containing subtrace from the error containing state of the error trace.

5. Concatenate error containing subtrace as a DTMC, and calculate its order as well as transition probabilities.

6. Determine the best fitting distributions of the length processes A_n and T_n .

Markov-based Trace Analysis (MTA) algorithm that extracts from an error traces a subset trace that has consistence properties. Modelling GSM wireless channel: Here characteristic statistics from a given trace using the MTA and Markov models [6].

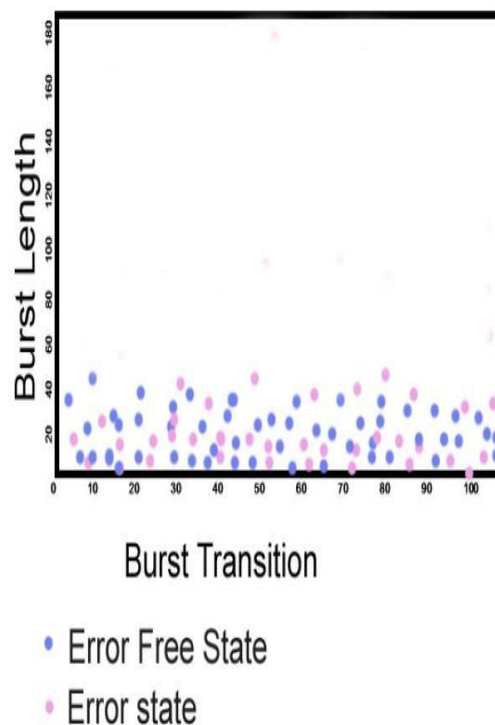


Figure 3. Burst length in error containing sub trace.

In this graphical representation, the average errorless burst is 3.32 frames, with a maximum value of 20 frames (recall as S value). In comparison, the errorless burst mean and maximum values in error containing sub-trace are much smaller than the error burst mean and maximum value in GSM trace. To prove that error containing subtrace is an consistence process we apply the Runs Test. (Figure) shows that 87.32% of the runs distribution lie between the 0.06 and 0.94 cut offs. Therefore, this result proves that error containing subtrace is a consistence process and can be modelled as a DTMC.

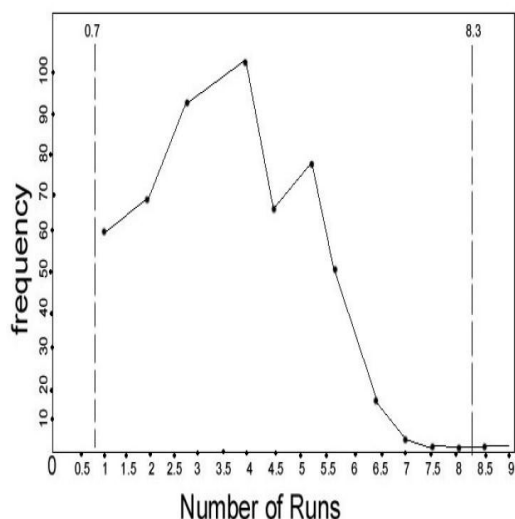


Figure 4. The Runs Test applied to error containing sub-trace

Conclusion

We compared GSM traces with MTA traces. We compared both the model in two forms, one is error burst length and another is Run test. We used same value of mean and s.d. In both type of comparison MTA have more consistency as compared to GSM traces. And have capability to generate more approximate traces of consistency nature.

References

[1] GSM Technical Specification 04.2, GSM Radio Protocol For telematic services, Version 6 .

[2] GSM Technical Specification 04.2, GSM Radio Protocol For telematic services, Version 6.3.

[3] M. Yajnik and D. Towsley, Packet loss correlation in the multicast environment: Experimental measurements chain models, S COMPSCI Technical report 95-105 (1993).

[4] M. Mouly and M.. Pautet, The GSM System for Mobile networks (Cell and Sys, jermany, 1992).

[5] ETSI GSM Technical Specification 03.2, Digital cellular mesh system (Phase 3+);

[6] B. Mandelbrot, S-s error group in communication systems and the concept of situational consistency, IEEE Transactions on Communication Technology COM-13 (1965).

[7] E GSM Technical Specification 4.8, Digital cellular communications system (GSM RLP) Channel coding, Version (may 2000).