On Loss Prediction for Real-time Packet Audio

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***Abstract*-- The effect of packet loss on the quality of real-time audio is significant. Nevertheless, Internet measurement experiments continue to show a considerable variation of packet loss, which makes audio error recovery and concealment challenging. In this poster we propose a novel technique to predict packet loss in real-time audio streams based on the one-way delay, inter-packet gap variation and delay trend, enabling proactive error recovery and congestion control for real-time audio over the Internet. Our preliminary simulation and experimentation results with various sites on the Internet show the high effectiveness and the accuracy of our loss predictor technique.**

***Index terms*-- multimedia, packet audio, loss prediction**

I. Introduction

Quality of Internet audio communication is highly sensitive to packet loss [3,8]. Majority of packet loss in the Internet occurs as the result of congestion in the links. Packet retransmission is not usually a viable option for real-time audio, since it adds to the delay that might exceed allowable mouth-to-ear delay bounds. Packet loss for audio is normally rectified by adding redundancy using Forward Error Correction (FEC) [4]. However, unnecessarily high degree of FEC can actually be detrimental rather than beneficial to the ongoing communication because of the excessive traffic. Here the challenge is to ensure a bandwidth-friendly transmission with an effective degree of loss recovery. That is possible if we can predict packet loss with a degree of certainty from the characteristics and the network dynamics of the ongoing transmission and perform proactive loss recovery using dynamic FEC. In this paper we investigate mechanisms to predict packet loss in real-time audio streams based on delay variation and trend, that will enable proactive error recovery and congestion/rate control for real-time audio over the Internet.

The basic idea of our proposed on-line loss prediction method is to successfully track the increase and decrease trends in one way delay and inter-packet gap, and accordingly predict the likelihood of packet loss due to congestion leading to lack of available bandwidth. However, this task becomes difficult due to the unpredictable and dynamic nature of cross traffic in the Internet. In this poster we attempt to formalize a framework to express the likelihood of loss in the next packet train in terms of (1) changes in the available bandwidth, manifested as end-to-end delay and inter-packet gap variations, and (2) near-past history of congestion in terms of short-term and long-term trends in delay variation. The value returned by the Predictor indicates the current degree and severity of congestion and lack of available bandwidth, hence the likelihood of packet loss, created by cross traffic bursts. The predictor value is fed back from the receiver to the sender in order for the sender to take proactive FEC actions and rate control. The reporting frequency of the predictor is dynamically adjusted in order to accommodate different RTT characteristics. This is superior to the static feedback such as RTCP currently used in adaptive mechanisms [1,2,5,7]. Also, the Predictor operates with dynamic packet window sizes based on the network conditions of the path.

II. Loss Predictor Formalization: An Overview

In the Predictor approach, we identify the minimum one way delay of a path as the baseline delay, signifying the delay under no congestion. We also identify the delay at the capacity saturation point of a path as the loss threshold, after which packet loss is more likely. We track the increase patterns or trends of the delay as an indication of congestion causing packet loss. In the Internet experiments that we have conducted [9], we have noticed that packet loss is usually preceded with a significant increase in end-to-end delay, and a range of loss threshold delay values after which loss is observed more often (Fig. 1- vertical lines denoting loss).

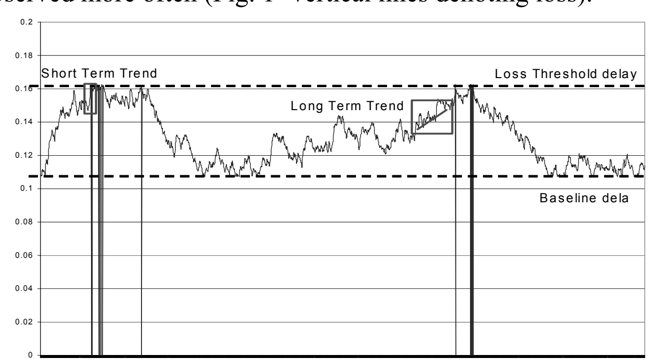

Figure 1: One Way Delay: Predictor components

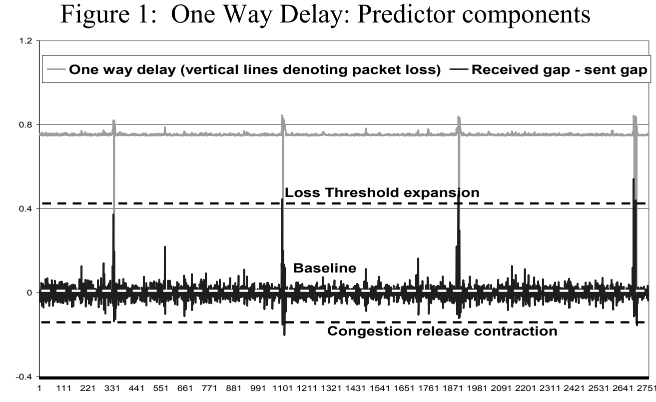

Figure 2: Inter-packet Gap: Predictor Components

Unlike the easily detectable baseline, the loss threshold delay shows a variety of ranges and behaviors due to the unpredictable nature of the cross traffic in the network. At the same time, discovering the packet drop thresholds with high confidence is crucial in determining the capacity saturation point of a particular path.

Detection of loss threshold in terms of one way delay is simple and straightforward, but the accuracy of this method is dependent on the degree of synchronization between the sender and the receiver clocks. In a parallel approach we track the changes in the inter-packet gaps as the packets are sent and received. When the received inter-packet gap is equal to the sent inter-packet gap of the CBR packets, it can be treated as the baseline gap, as it signifies the gap under no congestion. Congestion, due to the presence of a bottleneck link and/or variable cross traffic in the links constituting the path, manifests itself as various degrees of increase or decrease of the inter-packet gap deviating from the baseline, showing significant expansion and contractions before and after packet loss occurrences (Fig. 2). We track the variation patterns of the inter-packet gaps of the received packets as indications of congestion build-up and release, and accordingly predict the likelihood of packet loss by detecting loss threshold expansions and congestion release contractions.

The challenges of implementing a Predictor to derive the likelihood of packet loss from network measurements are as follows:

- To establish a range of delays that can be considered as the baseline delay for a particular path,
- To determine a range of delays and inter-packet gap expansions for loss thresholds,
- To find a likelihood of loss by detecting congestion from the measured increase ratio of delay and gap from baselines,
- To measure the trends in the delay increase; the likelihood of loss should also depend on the sharpness of delay increase, that is, how fast the delay is increasing,
- To detect congestion release from the delay decrease and inter-packet gap contraction patterns.

These challenges lead us to develop the Loss Predictor metrics. The metrics can be classified in three categories – (1) Delay/Gap Distance, (2) Short Term Trend and (3) Long Term Trend. Delay/Gap Distance gives an absolute ratio of the delay, gap expansion and contraction in relation to the baseline and loss thresholds. An example Delay Distance metric is as follows:

$$MinMaxOwd = \min\left(1, \frac{(D^k - base)}{(thr - base)}\right)$$

where
base = the minimum observed delay, or baseline
D^k = the delay value of the *k*-th packet,
thr = the threshold delay at which a loss is observed.

The Short-term Trend and the Long-term Trend metrics indicate the sharpness and consistency of upward and downward delay trends, and how fast the delay is increasing in short and long term window in terms of a number of past packets (Fig. 1). Whenever there is a sharp increase in the delay probably due to sudden burst of high degree of cross-traffic, there might be an occurrence of packet loss immediately after that (Fig. 1 – Short Term Trend). Short term trend metric tracks sharp changes in the delay, which is more critical for loss if the delay is close to the loss threshold. Sharpness Indicator (*SI*) is a Short Term metric that determines how fast the delay is approaching the loss threshold by measuring the slope of the line joining the delay values of the current packet and the previous packet.

$$SI = \max\left(-1, \min\left(1, (D^k - D^{k-1})/(t^k - t^{k-1})\right)\right)$$

In contrast, the long-term increasing trend tracks gradual rising trends due to persistent decrease in bandwidth, signifying gradual congestion build-up leading to packet loss (Fig. 1 – Long Term Trend). An example Long Term Trend metric is *Spct*, which indicates consistent increasing trend in a packet train as follows:

$$Spct = \frac{\sum_{k=2}^{\Gamma} I(D^k > D^{k-1})}{\Gamma - 1}, \quad I(X) = \begin{cases} 1 & if\ \ X\ holds \\ 0 & otherwise \end{cases}$$

By considering the rate of increase, the short-term and long-term metrics prevent Delay/Gap Distance metric from over-reacting to the absolute value of the delay and gap. Thus these metrics do not compete with each other, rather work complementary to one another. In the Loss Predictor approach we determine these metrics from the ongoing traffic and combine them with different weights based on their importance in order to estimate packet loss likelihood reliably.

We formalize the Loss Predictor as a weighted function of these three metrics. The loss predictor can be expressed as the following:

$$\begin{aligned}
&0 \le f(DelayGap, ShortTermTrend, LongTermTrend) \le 1 \\
&where \\
&f(DelayGap, ShortTermTrend, LongTermTrend) \\
&= w_1 * DelayGap + w_2 * ShortTermTrend + w_3 * LongTermTrend \\
&and \\
&w_1 + w_2 + w_3 = 1 \quad \text{....................(1)}
\end{aligned}$$

The Predictor uses dynamic weights w_1, w_2 and w_3 that depend on the current delay and congestion level.

III. Predictor Evaluation: Simulation Results

In this section we present the simulation results that evaluate the Predictor algorithm in terms of *accuracy* and *efficiency*. Ideally the predictor should behave accurately, that is, the predictor should report high values for the majority of packet loss occurrences. The predictor should also be efficient by not over-estimating when there is no loss. We used the network simulator ns-2 [6] to evaluate the Predictor algorithm under various network conditions.

We created two scenarios described in Fig 3. We assumed FCFS queuing and Droptail packet dropping for the links. In scenario 1, a CBR stream of 64kbps flowed from n_1 and n_2 through two intermediate hops, r_1-r_2 being the bottleneck link and four Pareto cross traffics flowed from n_3 to n_4 via r_1-r_2. In scenario 2, a CBR stream of 64kbps flowed from n_1 and n_2 through five intermediate hops (r_1, r_2, r_3, r_4 and r_5), and four Pareto cross traffics flowed from n_3 to n_4 via r_1-r_2, n_5 to n_6 via r_2-r_3, n_7 to n_8 via r_3-r_4, and n_9 to n_{10} via r_4-r_5 respectively. In both cases, we gathered a large set of data by introducing a varied number of transient cross traffics of different packet sizes and rates at dispersed points in time, causing different degrees of congestion resulting in stream packet loss at the intermediate links. The purpose of this experiment was to observe the delay-loss correlation patterns and loss threshold behaviors under a wide cross-traffic range and intermediate hop scenarios.

In Figs. 4 and 5 we present examples of simulation results from scenarios 1 and 2. All these figures show an identifiable baseline delay. The loss thresholds, on the other hand, vary from one another considerably. Scenario 2 has a wider loss threshold range and delay variation compared to scenario 1. This is due to variable and random degrees of cross traffic flowing through multiple links causing unpredictable congestion at different parts of the path. In contrast, congestion at one bottleneck link, though created by various degrees of cross traffic, produces more predictable results in scenario 1. In both scenarios, predictor value lies consistently between 0.75 and 0.92 around the loss regions, denoting high likelihood of packet loss, but decreases to low values in the range of 0 to 0.2 when the delay decreases close to the baseline. Thus the predictor successfully reacts to the baseline, loss threshold and increasing and decreasing trends of the delay in a wide variety of congestion situations.

Considering accuracy, the predictor value is greater than 0.6 87% in scenario 1 and 84% in scenario 2 around loss regions (Table I). Compared to scenario 1, we simulate more variable and random degrees of congestion at different parts of the path in scenario 2, but the predictor shows comparably robust accuracy under the variable congestion conditions. For efficiency we study the other side of the same coin, that is, how efficient the predictor is by not over-estimating when there is no loss. Both simulation scenarios show fair efficiency (72%-85%) by having predictor value less than 0.4 in 'non loss' regions (Table II). But it appears that the variable nature of cross traffic through many intermediate hops in scenario 2 causes increasing degree of 'False Alarm' (13%) of high predictor value in non-loss regions, resulting in less efficiency.

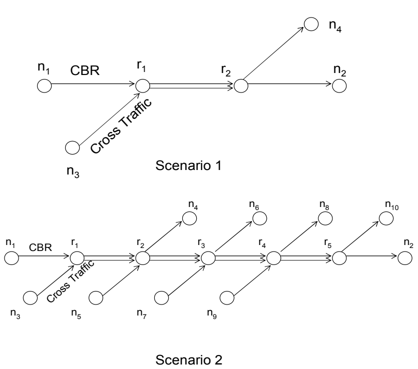

Figure 3: Simulation scenarios

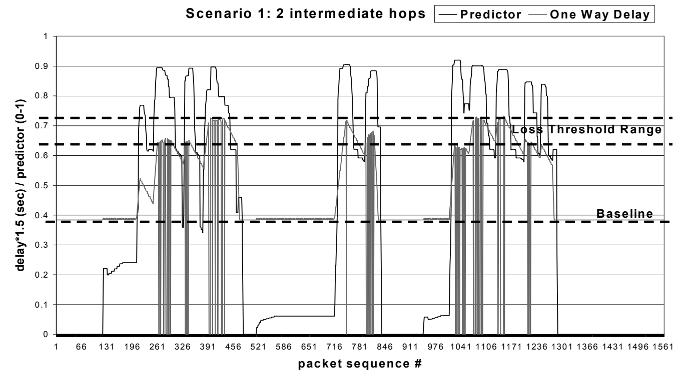

Figure 4: OWD, loss threshold and Predictor (Scenario 1)

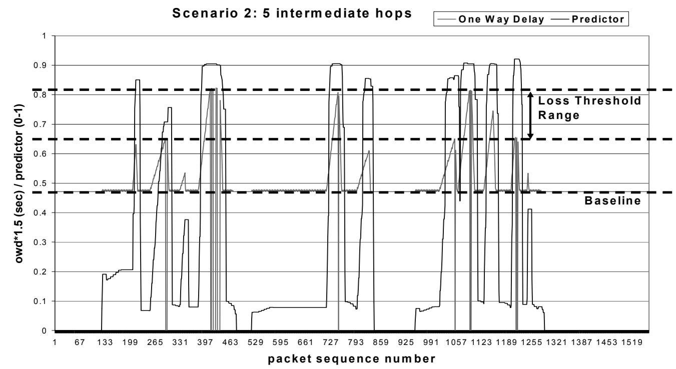

Figure 5: OWD, loss threshold and Predictor (Scenario 2)

TABLE I

Predictor Accuracy in Simulation Scenarios

Predictor value in 'around loss' region	Predictor value Percentage ratio	
	Scenario 1	Scenario 2
> 0.6	87%	84%
0.4 to 0.6	9%	4%
≤ 0.4	4%	12%

TABLE II

Predictor Efficiency in Simulation Scenarios

Predictor value in 'non-loss' region	Predictor value Percentage ratio	
	Scenario 1	Scenario 2
≤ 0.4	72%	85%
0.4 to 0.7	21%	2%
> 0.7	7%	13%

IV. Conclusion and Future Work

This poster presents a framework of a Packet Loss Predictor: a novel mechanism to predict packet loss in real-time audio streams by observing the delay and inter-packet gap variations and trends. Loss Predictor approach passively monitors path delay characteristics including one-way delay, inter-packet gap variation, and delay trends from the ongoing traffic, and combines these metrics with dynamic weights based on the current network condition, in order to derive a predictor value as the measure of packet loss likelihood. The Predictor value, fed back to the sender, indicates current degree and severity of congestion and likelihood of packet loss, and can be a vital component in sender-based proactive error and rate/congestion control mechanisms for multimedia. The dynamic adjustment of the reporting frequency and packet window sizes makes the framework superior to mechanisms with static feedbacks, and a viable technique for majority of network conditions.

The results of the Predictor under simulation scenarios and experiments show 84%-87% accuracy and 72%-85% efficiency. As future work, we need to improve the efficiency of the Predictor in order to use it as a self-feedback for prediction refinement in an ongoing basis. Formalization is also necessary for sender initiated proactive FEC and rate control actions, which depend on the Predictor feedback values.

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