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Statistical Characterization of QoS Aspects Arising From the Transport of Skype VoIP Flows

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***Abstract*—The analysis of QoE and QoS of adaptive real-time applications provides a challenging task in the current Internet. Here, we study major characteristics of Skype user satisfaction. For this purpose we estimate the loss and delivery time variation by inter-arrival times (IAT) between packets and packet lengths (PL) of an individual unidirectional flow. Extremes of the IAT and PLs impact on the QoS profile. We propose the estimates of the mean delivery time variation of complete packets per cluster, that influences the mean delay variation, the overall and mean byte losses, the required channel capacity to provide a desirable loss rate and the corresponding quantiles of a lossless period.**

***Index Terms*—Skype VoIP flows, statistical traffic characterization, QoS analysis**

I. Introduction

The transition from TDMA-based voice transport to IP-supported voice transfer through the Internet has generated an increasing interest in teletraffic engineering. In recent years, Skype has become a powerful service platform for the generation and transport of voice over IP (VoIP). The application of its variable bitrate encoding and the packet-based voice transfer raises new questions regarding traffic characterization.

Following [5] we study passive Skype measurements at the packet layer. We have measured individual unidirectional Skype flows arising from a representative WLAN network scenario of a point-to-point communication between two individual Skype users. The objective is to evaluate the mean delivery variation of complete packets and loss which impact on the user satisfaction. In [5] the bitrate, jitter and round-trip time are selected as factors that impact on the call duration and, hence, the user satisfaction. However, the call duration may only reflect the user behavior and cannot be considered as a direct indicator of the user satisfaction. We investigate the IATs between received Skype packets and PLs which reflect the user activity. The PL interrelates with the bitrate and influences on the loss. The IATs interrelate with the delay variation and loss and, hence, influence on the QoS and QoE. In contrast to [3], where the IATs are assumed to be Gaussian distributed despite of their recognized high variability, we do not avoid the heavy-tailed nature of IATs. In [9] we have found that the IATs of packets of an underlying individual unidirectional flow constitute a self-similar, moderate long-range dependent (LRD) and heavy-tail distributed sequence with a finite variance. Any statistical analysis of Skype data is complicated due to the presence of non-stationarity and dependence in the data. In [5] the original series is divided into sub-series of a fixed length since the extreme conditions may influence on the user behavior more than ordinary conditions. The maximum bitrate and minimum jitter are chosen within selected time windows. Following this line, we propose to partition the IATs into subsets of unequal size in such a way that these subsets are independent. For this purpose we apply a quantile method proposed in [10]. Then exceedances of the IATs over a sufficiently high quantile of the IATs indicate the boundaries of these subsets. We consider independent representatives of each subset, i.e. maxima of PLs as well as maxima and minima of IATs within subsets as QoS factors. These extremes should form stationary sequences. The independence and stationarity features allow us to estimate the high quantiles of these indices close to 100% which indicate the most likely upper bounds. These bounds may exceed the corresponding sample characteristics observed in the data and influence on the delay and delivery variations and loss of the transfer. We estimate the mean delivery variation of complete packets per cluster, the overall and mean byte losses and the required channel capacity to provide a desirable overall byte loss and the corresponding quantiles of a lossless period.

The proposed common methodology demonstrated by an individual packet flow can be similarly applied to other flows including aggregated streams which is the ultimate goal of VoIP traffic engineering. Due to the linearity of estimates one can also organize an on-line analysis. The values obtained here by the concrete flow may not be valid for other flows.

The paper is organized as follows. In Section II a description of the Skype data is stated. In Section III the partitioning of the IATs into independent subsets is provided. In Section IV the stationarity of extremal values of the PLs and IATs within subsets is proved. An analysis of quality and load aspects by means of high quantiles of extremes of PLs and IATs and the estimation of the mean delivery variation of complete packets per cluster are given in Section V. The estimation of the overall and mean byte losses, the required capacity of a channel and quantiles of a lossless period are stated in Section VI. Finally, some conclusions are presented.

II. Peer-to-peer VoIP transport by Skype and description of the Skype data

Due to the peer-to-peer nature of Skype, one cannot monitor the traffic of any two hosts in the world. Hence, one must gather the Skype traffic related to a particular site, cf. [5].
To analyze the features of Skype VoIP traffic, we have set up different prototypical scenarios between two Skype clients within a LAN testbed at Otto-Friedrich University Bamberg in 2006. The data set that will be used here to illustrate the typical features of Skype flows has been arising from a transmission path with several wired and two wireless links where both the sending mobile client (mobile host 2 at 192.168.182.22) and the receiving mobile client (mobile host 1 at 192.168.1.4) are first traversing private IEEE802.11 WLAN segments 1 and 5, respectively, with DSL attachments to the public Internet and then an Internet path 2,3,4 including a tier-1 carrier exchange point between Telefonica's and Deutsche Telekom's ISP networks (see Fig. 1). This network path can be considered as typical VoIP over WLAN environment that a majority of Skype users traverse today. The data used here were gathered by an Ethereal monitor at the receiver 192.168.1.4.
To study the impact of wireless links on the quality of Skype flows, further scenarios with wired attachment of the sending and receiving clients to the DSL lines have been analyzed as well but cannot be discussed here due to space limitation.
In all cases we have monitored the arising packet flow of Skype encoded voice samples of a single communication session between the involved clients. The latter has been generated based on a mixture of short representative sessions of monologues, dialogs and music clips with German and English male and female speakers and lasts 135 seconds. Then the resulting unidirectional packet streams have been isolated. They have been analyzed by statistical means to understand the features of Skype traffic and to lay the foundation for a mathematically rigorous development of teletraffic models regarding P2P VoIP traffic of an adaptive VBR coding scheme

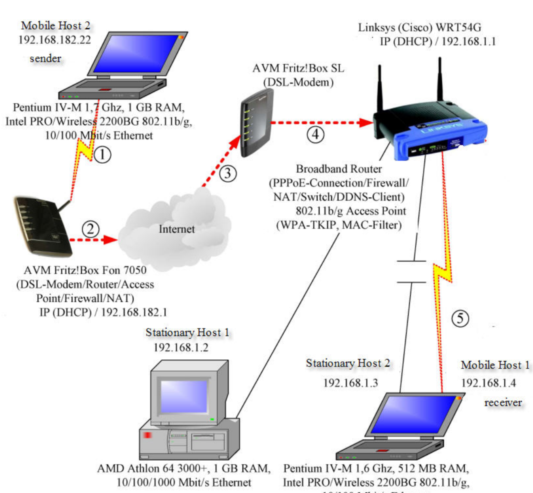


Fig. 1: LAN testbed for voice communicaton by Skype clients.

TABLE I: Description of the Data Arising from a Skype Flow.

R.V.	**Sample Size**	**Min**	**Max**	**Mean**	**StDev**
Inter-arrival times (sec)	4605	1.9 $\cdot 10^{-5}$	2.01 $\cdot 10^{-1}$	3.1 $\cdot 10^{-2}$	8.635 $\cdot 10^{-3}$
Packet lengths (bytes)	4605	45	284	160.27	25.808
Maxima of inter-arrival times (sec)	72	5.8 $\cdot 10^{-2}$	2.01 $\cdot 10^{-1}$	7.3 $\cdot 10^{-2}$	2.6 $\cdot 10^{-2}$
Minima of inter-arrival times (sec)	72	1.9 $\cdot 10^{-5}$	9.1 $\cdot 10^{-2}$	3.3 $\cdot 10^{-2}$	6.816 $\cdot 10^{-4}$
Maxima of packet lengths (bytes)	72	85	284	197.69	1688

like iSAC used by Skype which responds to varying network conditions.
To illustrate our methodology we have used the flow data of the wireless testbed and investigated the IATs between Skype packets and the PLs. To evaluate the load and delivery variation profile, we need the extremes of PLs and IATs within independent subsets (blocks) of data. Their descriptive statistics are stated in Table I. The subsets are determined in Section III.

III. Partitioning of IATs into independent subsets

Considering the investigation of a process that might be non-stationary, it is a standard tool to partition the data into disjoint independent subsets. According to [10] one can use the exceedances over some empirical quantile of the data as boundaries between these subsets. The subsets are usually not of equal lengths. Here we partition the IATs between Skype packets, $X_1, ..., X_n$, where n is the sample size, into subsets and calculate the cumulative inter-arrival lengths within these subsets, $L_j = \sum_{i=k_j}^{k_j-1+N_j} X_i$, $j = 1, ..., N_s$. N_j is the random size of the jth subset depending on the quantile of X_i, $N_0 = 0$, and $k_j = \sum_{m=0}^{j-1} N_m + 1$ is the number of the first IAT in the jth subset. To generate a sufficient number $N_s = 72$ of independent subsets, we use the minimal possible 98.4% empirical quantile of IATs equal to 0.057, see Fig. 2. To approve the independence of lengths of subsets, $L_1, ..., L_{N_s}$ arising from these subsets we have to check first whether the variance of the data is finite. This is necessary to apply an appropriate test. If the distribution of the underlying random sequence is regularly varying, the resulting distribution

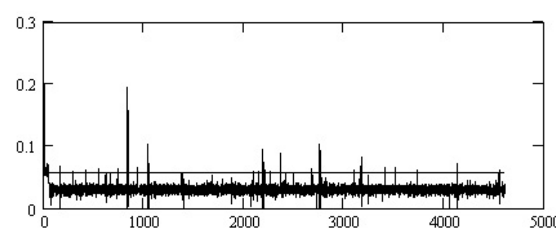


Fig. 2: The inter-arrival times between Skype packets and their 98.4% quantile (solid horizontal line).

function (DF) is determined by $F(x) \sim 1 - cx^{-\alpha}$, $\alpha > 0$. [1] The parameter α shows the heaviness of the tail and indicates the number of finite moments of the distribution. The βth moment is finite if $\beta < \alpha$ and infinite otherwise. The mean excess function, $e(u) = \mathbb{E}(X - u|X > u)$ is one of the tools that may indicate the heavy-tailed distribution of the lengths of subsets, $\{L_i\}$. The increase (or decrease) of $e(u)$ implies a heavy-tailed (or light-tailed) distribution. Its constant value corresponds to an exponential distribution. Its linear increase indicates a Pareto-like distribution. In Fig. 3(a) we show its sample estimate

$$e_n(u) = \sum_{i=1}^{n}(X_i - u)\mathbf{1}(X_i > u)/\sum_{i=1}^{n}\mathbf{1}(X_i > u) \qquad (1)$$

for various thresholds u and the underlying sequence of the lengths of subsets, $\{L_i\}$. One may conclude that the distribution of the lengths of subsets might follow a mixture of Pareto and exponential increments with domination by Pareto at the tail.

Here we estimate the tail index α or the extreme value index (EVI) $\gamma = 1/\alpha$ by the well-known Hill's, ratio and moment estimators, cf. [8]. The Hill's estimator

$$\hat{\gamma}^H(n, k_0) = \frac{1}{k_0}\sum_{i=1}^{k_0}\ln X_{(n-i+1)} - \ln X_{(n-k_0)}, \quad (2)$$

where $X_{(1)} \le X_{(2)} \le \ldots \le X_{(n)}$ are the order statistics of the sample, $X_1, X_2, \ldots, X_n$ and k_0 is a smoothing parameter, and the ratio estimator

$$a_n(x_n) = \sum_{i=1}^{n}\ln(X_i/x_n)\mathbf{1}\{X_i > x_n\}/\sum_{i=1}^{n}\mathbf{1}\{X_i > x_n\}, \quad (3)$$

where x_n is an arbitrary threshold, are only appropriate for a positive γ which corresponds to a heavy-tailed distribution. In contrast to that, the moment estimator

$$\begin{aligned}\hat{\gamma}^M(n, k_0) &= \hat{\gamma}^H(n, k_0) + 1 \quad (4)\\ &\quad -0.5\left(1 - (\hat{\gamma}^H(n, k_0))^2/S_{n,k_0}\right)^{-1},\end{aligned}$$

where $S_{n,k_0} = (1/k_0)\sum_{i=1}^{k_0}\left(\log X_{(n-i+1)} - \log X_{(n-k_0)}\right)^2$, is valid for any real valued γ that may correspond to light-tailed distributions in case of negative values, cf. [8]. However, $\hat{\gamma}^M(n, k_0)$ has a larger variance than the first two estimates.

We have computed the non-asymptotic confidence intervals of the Hill's and ratio estimates $\hat{\gamma}$ by the formula

$$I_\varepsilon = [\hat{\gamma}/(1 + y_\epsilon M_n^{-1/2}); \hat{\gamma}/(1 - y_\epsilon M_n^{-1/2})], \quad (5)$$

given in [11]. Here $M_n = \sum_{i=1}^{n}\mathbf{1}\{X_i > u\}$ denotes the number of exceedances over the threshold u for the underlying sequence $\{X_i\}$, $i = \overline{1, n}$, and y_ϵ is calculated as a quantile of the standard normal distribution, $\Phi(x)$, namely, $\Phi(-y_\epsilon) = (\epsilon/2 - C_* M_n^{-1/2})_+$ (we take only the positive difference). $C_* < 0.8$ is a constant arising from the Berry-Esséen inequality. We select $\epsilon = 0.05$ and C_* such that the

[1]A Pareto distribution gives an example of such distribution.

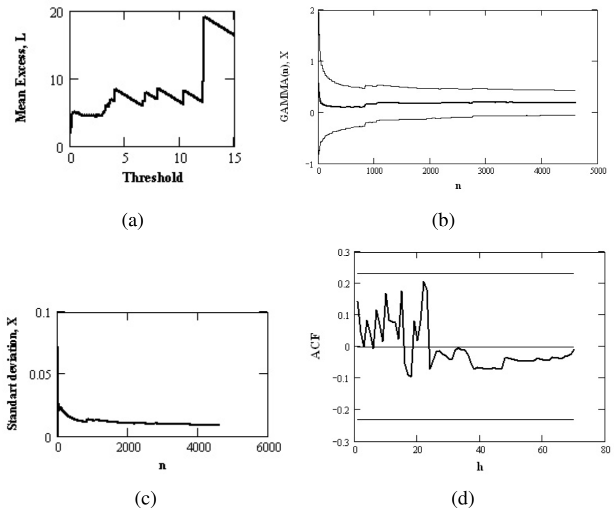


Fig. 3: The mean excess function of the lengths of subsets, $\{L_i\}$ (a), the Hill plot with asymptotical 95% Gaussian confidence interval (b) and the standard deviation (c) of inter-arrival times between Skype packets against the number of observations n. The standard deviation converges to a finite value as n increases. The ACF of the lengths of the subsets obtained by 98.4% quantile exceedances with normal 95% bounds (d).

narrowest confidence interval is provided.

For the moment estimator the asymptotic 95% Gaussian confidence interval $[\hat{\gamma} - 1.96/\sqrt{k_0}, \hat{\gamma} + 1.96/\sqrt{k_0}]$ is calculated. The results are summarized in Table II. One may conclude that the variance of the cumulative inter-arrival lengths of subsets might be infinite since $1 < \alpha < 2$.

Remark 1: It is shown in [9] that the IATs are moderate LRD and heavy-tailed with $\alpha > 2$. The existence of a finite variance of IATs may be supported by plotting the "running moment estimates" and the "running tail index estimates" following the line of [15], see Fig. 3(c), 3(b).[2] We have shown that the lengths of subsets, $\{L_i\}$ which are the sums of the corresponding IATs have a heavy-tailed distribution with infinite variance and finite mean. If the IATs were independent then the lengths of the subsets could be normal distributed according to the central limit theorem. The infinite variance may be caused by the dependence of IATs and a specific distribution of the random number $\{N_j\}$ of IATs in the subsets. Hence, an appropriate model of the IAT process should satisfy an LRD property (i.e., $\sum_{h=0}^{\infty}|\rho_X(h)| = \infty$, where $\rho_X(h) = \mathbb{E}\left((X_t - \mu)(X_{t+h} - \mu)\right)/\sigma^2$ is the autocorrelation function (ACF)) and the lengths of subsets, $\{L_j\}$ should follow a heavy-tailed distribution with infinite variance.

Now we shall check the independence of the lengths of subsets. Although the ACF at lag h is not defined due to the

[2]A parameter or a moment estimate is plotted against the increasing number of observations used in the estimation. If the first moment of the distribution is finite, the sequential mean plot converges to the true value of this mean.

TABLE II: Estimates of the Extreme Value Index γ with 95% Confidence Intervals of Skype Flow Characteristics.

	Hill's Estimate	**Ratio Estimate**	**Moment Estimate**
Inter-arrivals (sec)	0.344 $[-0.146, 0.834]$	0.4 $[0.284, 0.465]$	0.4 $[-0.291, 0.689]$
Lengths of subsets (sec)	0.641 $[0.516, 0.845]$	0.681 $[0.55, 0.894]$	0.676 $[0.201, 1.152]$
Maxima of inter-arrival times (sec)	0.224 $[0.185, 0.283]$	0.218 $[0.18, 0.275]$	0.429 $[0.103, 0.756]$
Minima of inter-arrival times (sec)	0.123 $[0.102, 0.156]$	0.122 $[0.099, 0.157]$	-0.089 $[-0.447, 0.269]$

infinite variance of $\{L_i\}$, one can use the classical formula for a sample ACF

$$\widehat{\rho}(h) = \sum_{t=1}^{n-h}(X_t - \overline{X}_n)(X_{t+h} - \overline{X}_n)/\sum_{t=1}^{n}(X_t - \overline{X}_n)^2 \quad (6)$$

of $\{L_i\}$ with $1 < \alpha < 2$, cf. [12, p.349]. However, it is difficult to check the null hypothesis that the data stems from an i.i.d. sample of a heavy-tailed distribution because the confidence intervals of the ACF are not exactly defined in contrast to the Bartlett's Gaussian 95% bounds $\pm 1.96/\sqrt{n}$ of the $\widehat{\rho}(h)$ corresponding to the case of a finite variance, see [4]. Looking at $\widehat{\rho}(h)$ of $\{L_i\}$ one may conclude that the i.i.d. hypothesis could be accepted since the ACF is close to zero for large lags and falls within the normal confidence bounds, see Fig. 3(d). Due to the infinite variance we cannot apply the well-known Ljung-Box Portmanteau test to check the independence of the lengths of subsets, $\{L_i\}$ obtained by 98.4% quantiles of IATs, cf. [4], [7]. According to this test, the statistic

$$Q = n(n+2)\sum_{j=1}^{h}\hat{\rho}^2(j)/(n-j) \quad (7)$$

has approximately a chi-square distribution with h degrees of freedom in case of a process with a finite variance. The i.i.d. hypothesis should be rejected at level η if $Q > \chi^2_\eta(h)$, where $\chi^2_\eta(h)$ is the ηth quantile of the chi-square distribution with h degrees of freedom, i.e., $Pr\{\chi^2 > \chi^2_\eta(h)\} = \eta$, $0 < \eta < 1$.

Remark 2: When empirical quantiles lower than 98.4% (e.g., 97%) are used to select the subsets, the resulting $\{L_i\}$ have a finite variance (Hill's estimate $\hat{\alpha} = 1/\widehat{\gamma} > 2$, see Table III). However, the Ljung-Box test rejects the i.i.d. null hypothesis at level 5% for these smaller subsets, see Table III.

We apply Runde's test [13] for $1 < \alpha < 2$ that uses the statistic

$$Q_R = (n/\ln n)^{2/\alpha}\sum_{j=1}^{h}\hat{\rho}^2(j). \quad (8)$$

TABLE III: Ljung-Box Test Results.

Subsets Selection	$\widehat{\gamma}$	**Lags**	**Q**	$\chi^2_{0.05}(\mathbf{h})$
97% quantile	0.34	10	49.707	18.3
		20	62.549	31.4
		30	73.481	43.8

TABLE IV: Runde's Test Results.

Method of Subsets Selection	**Lags**	$\mathbf{Q_R}$	$\mathbf{Q_h(0.05)}$
98.4% quantile	2	10.257	13.53
	3	11.877	16.32
	4	15.481	18.28
	5	17.975	19.17

Q_R has a limiting distribution of a stable type subject to the assumption that the underlying sequence belongs to the domain of attraction of a symmetric α-stable distribution with $1 < \alpha < 2$. In [6] it is shown by simulation that Runde's test is more powerful than the alternative covariation tests if $\alpha \le 1.6$ holds. According to Table II the lengths of subsets possess such α. Since $\{L_i\}$ are positive and heavy-tailed their distribution cannot be symmetric. To use Runde's test we have to construct a new symmetric r.v. For this purpose, we consider $Y_i = s_i L_i$, where s_i is a discrete r.v. that takes the values $+1$ and -1 with probability 0.5. Y_i has the same tail index α as L_i since the DF of Y_i is determined by

$$\mathbb{P}\{Y_i \le x\} = 1/2\mathbb{P}\{|s_i L_i| \le x\} = 1/2\mathbb{P}\{L_i \le x\}. \quad (9)$$

Now we can check the independence of Y_i. If $\{Y_i\}$ are independent then $\{L_i\}$ are independent, too, since it holds

$$\begin{aligned} & 1/2^n\mathbb{P}\{L_1 \le x_1\}...\mathbb{P}\{L_n \le x_n\} \quad (10) \\ = \ & \mathbb{P}\{Y_1 \le x\}\ldots\mathbb{P}\{Y_n \le x\} \\ = \ & \mathbb{P}\{Y_1 \le x_1, ..., Y_n \le x_n\} \\ = \ & \mathbb{P}\{s_1L_1 \le x_1, ..., s_nL_n \le x_n\} \\ = \ & 1/2^n\mathbb{P}\{|s_1L_1| \le x_1, ..., |s_nL_n| \le x_n\} \\ = \ & 1/2^n\mathbb{P}\{L_1 \le x_1, ..., L_n \le x_n\}. \end{aligned}$$

The results of Runde's test are summarized in Table IV. Since $\widehat{\alpha}$ of L_i varies between 1.468 and 1.56 according to Table II, we take $\alpha = 1.5$ to compare the values of Q_R with the critical values $Q_h(0.05)$ of the limiting distribution of Q_R for the 0.05-level given in [13]. Since the values Q_R do not exceed $Q_h(0.05)$, the null hypothesis regarding the independence of L_i should be accepted. Thus, we have shown the independence of the cumulative inter-arrival lengths within subsets, L_i.

IV. Testing the Stationarity

We check the stationarity of representative statistics within the independent subsets by an inversion test, cf. [2]. The null hypothesis states that the underlying sequence contains independent stationary random observations, i.e., a trend does not exist. For this purpose one calculates the statistic $A = \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\mathbf{1}(X_i > X_j)$. The hypothesis is accepted at level $\alpha = 0.05$ if $A_{n,1-\alpha/2} < A \le A_{n,\alpha/2}$, where $A_{n,1-\alpha/2}$ and $A_{n,\alpha/2}$ are quantiles of the DF of A. The bounds of A are given by $[1014, 1400]$.

We investigate the stationarity and independence of the maxima of PLs and the increments, $X_t - X_{t-1}$ of maxima and minima of IATs between Skype packets in the subsets. Since the values of A fall into the mentioned interval the null hypothesis should be accepted for maxima of PLs as well as maxima and minima of IATs (see Table V).

TABLE V: Inversion Test Results.

	Maxima of Packet Length	**Increments of Inter-arrival Times**	
		Maxima	*Minima*
A	1358	1294	1249

V. Analysis of QoS and Load Aspects

The load may be characterized by the PLs and IATs between Skype packets. We estimate the high quantiles close to 100% of the minimal and maximal IATs and maximal PLs. We use the well-known high quantile estimate of level $1-p$, cf. [14],

$$x_p^w \quad = \quad X_{(n-k_0)}\left((k_0+1)/((n+1)p)\right)^{1/\hat{\alpha}}, \qquad (11)$$

$k_0 = \overline{1, n-1}$. $\hat{\alpha}$ is some estimate of the tail index, e.g., the Hill's estimate. k_0 is the number of the largest order statistics arising from the underlying random sequence $X_1, ..., X_n$. One can use the same k_0 both for $\widehat{\gamma}^H(n, k_0)$ and x_p^w. The stationarity and independence of $X_1, ..., X_n$ constitute the main assumptions of this estimate. These properties of the maxima of the PLs as well as the maxima and minima of the IATs were approved in Section IV. The extremes of the IATs within independent subsets that were obtained in Section III are evidently independent. To be sure that the maxima of the PLs are independent, we estimate the extremal index $\theta \in [0, 1]$, see Fig. 4. It indicates the change in the limiting distribution of the maxima due to dependence in the sequence, cf. [1]. For independent identically distributed sequences $\theta = 1$ holds. $1/\theta$ relates to the mean number of exceedances per cluster, cf. [1]. Regarding the blocks estimate

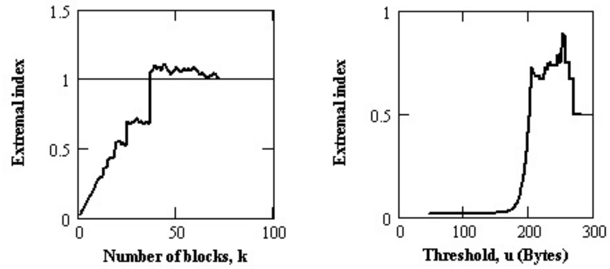
$$\overline{\theta}^B(u) \quad = \quad \frac{n\sum_{j=1}^{k}\mathbf{1}(M_{(j-1)r,jr} > u)}{rk\sum_{i=1}^{n}\mathbf{1}(X_i > u)} \qquad (12)$$

of θ, the cluster is a block of data with at least one exceedance over a threshold u, $M_{i,j} = \max(X_{i+1}, ..., X_j)$, k is the number of blocks, $r = [n/k]$ is the number of observations in each block, $[\cdot]$ denotes the integer part of the number. For the number of blocks equal to 72, $\overline{\theta}^B(u^*)$ is equal to 1. This implies that the maxima of the PLs corresponding to our 72 subsets are independent. u^* has been taken equal to the mean of the maxima 197.69 of the PL. The original PLs are dependent since the scene blocks estimate [10]

$$\overline{\theta}_S^B(u) \quad = \quad \frac{\sum_{j=1}^{k}\mathbf{1}(M_{\sum_{m=0}^{j-1} r_m, \sum_{m=1}^{j} r_m} > u)}{\sum_{i=1}^{n}\mathbf{1}(X_i > u)}, \qquad (13)$$

of θ is less than 1 for any u, see Fig. 4. $\overline{\theta}_S^B(u)$ allows us to avoid the selection of the block size r. r_j is the number of packets in the jth subset, $\sum_{j=1}^{k} r_j = n$, $r_0 = 0$, k is the number of subsets. The subsets obtained in Section III are used as data blocks.

x_p^{ω} and 90% non-asymptotic bootstrap confidence intervals of its logarithm (see, [8, p.172]) are given in Table VI. The number of bootstrap re-samples has been taken equal to 100. The high quantiles of the extremal IATs and PLs reflect the upper bounds of these indices which can be exceeded with small probabilities. The small IATs are typical for frequently incoming packets. Together with large PL they may lead to an overload of a wireless link to a mobile client. Large IATs are not dangerous regarding the overload effect but may lead to a poor quality of the voice transmission due to the exceedance of the stringent delay requirement of 150 ms at the receiver.



(a) (b)

Fig. 4: Estimation of the extremal index of the maximal PLs within independent subsets by the blocks estimator (4(a)) and the original PLs by the scene blocks estimator (4(b)).

TABLE VI: High Quantile Estimation of Minimal and Maximal Inter-Arrival Times and Maximal Packet Lengths with 90% Bootstrap Confidence Intervals of $\log(x_p^w)$.

R.V.	$(\mathbf{1-p})\cdot\mathbf{100}\%$	$\mathbf{x_p^w}$ ($\log(\mathbf{x_p^w})$)	**Confidence interval**
Maximal packet length (bytes)	99	312.727 (2.495)	$(1.983, 2.963)$
	99.9	408.881 (2.612)	$(2.078, 3.112)$
Maximal inter-arrival time (sec)	99	0.154 (-0.811)	$(-1.083, -0.631)$
	99.9	0.258 (-0.588)	$(-0.969, -0.399)$
Minimal inter-arrival time (sec)	99	0.082 (-1.087)	$(-1.473, -0.709)$
	99.9	0.109 (-0.964)	$(-1.703, -0.201)$

Let us use a bufferless fluid model and assume that the packet stream is approximated by a continuous flow. Its rate is determined by the ratio of the PL Y_i per IAT X_i, i.e. $R_i = Y_i/X_i$, $i = 1, \ldots, n$. It is supposed to be constant between arrivals and only changing at arrival epochs. Then the IATs at departure show the delivery variations of all packets including not completely delivered ones. Table VI shows that the maximal and minimal delivery variations of packets are less or equal to 154 ms and 82 ms, respectively, with probability 99%.

The exceedances of PLs over a threshold u cause loss and delay due to packets delivered not completely. One can estimate the mean delivery time variation of complete packets per cluster (i.e. the mean inter-arrival time of completely transmitted packets) by $d = (1+1/\theta)\mathbb{E}X$. $1/\theta$ indicates the mean number of not completely delivered packets (exceedances over the threshold) between any two adjacent completely transmitted packets. $\mathbb{E}X$ is the mean IAT. d may be estimated by $\widehat{d} =$

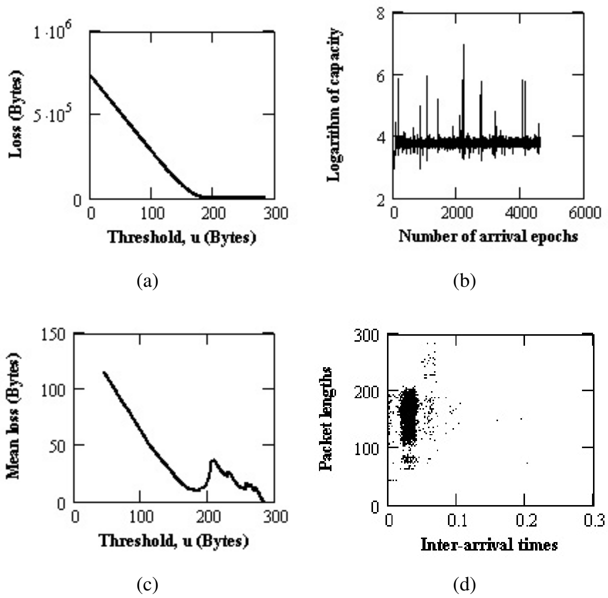


Fig. 5: Estimation of the overall byte loss $E(u)$ (a). The logarithm of the bottleneck capacity in Kbps required to have an overall byte loss of 3% (b). The mean byte loss $e_n(u)$ (c) and the scatter plot of PLs against IATs (d).

$(1+1/\overline{\theta}_S^B(u))\overline{X}$. $\widehat{d} = 1.059$s arises for $u = u^{**}$ corresponding to 3% overall byte loss (see Section VI), $\overline{X} = 31$ms, and the independent subsets obtained in Section III as data blocks. The clusters are the main source of delivery variation since $\widehat{d}$ is larger than the maxima of the IATs.

VI. Loss and capacity estimation

Regarding the loss estimation we use a bufferless fluid model again. The overall byte loss, $E(u) = \sum_{i=1}^{n}(Y_i - u)\,\mathbf{1}(Y_i > u)$ for an observation time is generated by exceedances of the PLs, $\{Y_i\}$ over a threshold u given in bytes, see Fig. 5(a). The loss decreases if u increases. Since the maximal PL is equal to 284 bytes there is no loss for $u = 284$ bytes. $u^{**} = 169.895$ bytes leads to an overall byte loss of 3%. The resulting capacity corresponding to the gross rate on the physical link is calculated by u^{**}/X_i and its mean value is equal to 10 kb/s, see Fig. 5(b). The mean byte loss is determined by the mean excess function, $e(u)$. It indicates the mean loss due to the exceedances of the PLs over u. Fig. 5(c) shows its sample estimate, $e_n(u)$. $e_n(u)$ tends to increase for $u \in [180, 210]$. This corresponds to a large number of packets whose lengths exceed such u, see Fig. 5(d). The degree of user dissatisfaction is driven by the bottleneck capacity corresponding to u. $e(u)$ does not depend on the frequency of received packets that is determined by the IATs. The inter-exceedance times (IET) that can be larger than the IATs express lossless periods. The empirical $\{50, 75, 80, 85, 95, 97.5\}\%$ quantiles of the IETs arising from exceedances of PLs over u^{**} are equal to $\{38, 68.2, 88.05, 112.5, 205, 330\}$ ms, respectively. It implies that the loss-free time exceeds these values with the probabilities $\{50, 25, 20, 15, 5, 2.5\}\%$ and the corresponding overall loss is equal to 3%.

VII. Conclusion

We have considered the packetized transport of voice samples that are arising from an adaptive network-aware variable bitrate encoder like Skype's iSAC codec. We have shown the impact of the IATs and PLs of Skype packets and the channel capacity on the loss and delivery variation of the Skype packet transfer and, hence, on the user satisfaction. The methodology is illustrated by an individual unidirectional flow. Since the extremal values of the IATs and PLs may cause high delivery variation and loss (e.g. frequent large packets or very rare packets) their high quantiles have been estimated. These quantiles provide the values of the extremes that may be exceeded with a small probability. The estimation of the mean delivery of complete packets per cluster as well as the overall and mean byte losses have been worked out. We have also determined the choice of the channel capacity corresponding to a maximal allowed loss. The corresponding quantiles of a lossless period that reflect the quality have been computed, too. The proposed methodology can also be applied to aggregated traffic in an on-line regime.

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