Video Quality Monitoring based on Precomputed Frame Distortions

Dominik Klein, Thomas Zinner, and Stanislav Lange
University of Wuerzburg
Email: {dominik.klein, zinner, stanislav.lange}@informatik.uni-wuerzburg.de

Vlad Singeorzan and Matthias Schmid
Infosim GmbH & Co. KG
97076 Wuerzburg
Email: {singeorzan,schmid}@infosim.de

***Abstract*—In the past decade, video streaming has taken over a large part of the current Internet traffic and more and more TV broadcasters and network providers extend their portfolio of video streaming services. With the growing expectations of video consumers with respect to the service quality, monitoring is an important aspect for network providers to detect possible performance problems or high network load. In parallel, emerging technologies like software defined networking or network virtualization introduce support for specialized networks which allow enhanced functionality in the network. This development enables more sophisticated monitoring techniques in the specialized networks which use knowledge about the video content to better predict the service quality at consumers. In this work, we present a content-aware SSIM-based monitoring technique and compare it with the current state-of-the art which infers the service quality from the monitored packet loss. We further show how network conditions like packet loss or bursts influence the two different monitoring techniques.**

I. Introduction

Recent studies [1] prove the growing importance of video streaming via IP networks. This includes IPTV solutions where videos are typically transmitted in a multicast fashion via dedicated networks using connectionless transport protocols like RTP/UDP. In parallel, emerging technologies like software defined networking or existing technologies like network virtualization enable application specific networks by creating virtual networks above a physical substrate. Related concepts and business roles in a virtualized environment have been studied in an earlier work [2]. Physical infrastructure providers (PIPs) own and operate the hardware and offer virtualized resources. Virtual network providers (VNPs) gather these virtual resources and construct virtual networks. Finally, virtual network operators (VNOs) request application specific networks with special requirements, e.g. setting up a service level agreement (SLA) and ramp up the network, i.e. install hosts, define protocols, and control the network. In such a virtualized architecture, application specific virtual networks may span several physical networks under different administrative domain. These physical domains could comprise cloud or data center networks, best-effort transport networks as well as customer access networks. The VNO operates the virtual network which is for example tailored to accommodate a video streaming service and must ensure a good service quality. This requires an application aware monitoring which enables the VNO to detect possible performance problems and to identify, which physical domain is responsible. Up to now, the monitoring of video streaming services usually only involves simple performance metrics like consumed bandwidth, packet loss, or experienced delay or jitter for the customers. However, these simple metrics are not sufficient to accurately predict the quality of experience at the end user under the current network situation. For that, user-centric monitoring techniques are required which for example utilize content-specific information to predict the experienced service quality at the customers. In this work, we present a user-centric monitoring technique which uses precomputed knowledge about the video content to assess the service quality of video consumers. The proposed monitoring technique takes into account the quality degradation due to lost frames and stores that information on monitoring nodes in the network. The computation is based on the structural similarity (SSIM) [3] metric and uses a mapping from SSIM to video quality in order to predict the quality at the video consumer. The remainder of this paper is structured as follows. In Section II, we present related work and explain differences to our approach. Section III explains the foundation for our monitoring approach and gives functional details. Section IV introduces the used environment for the evaluation and in Section V, we compare our proposed monitoring technique with the current state of the art in video monitoring and highlight, in which scenarios our proposed solution outperforms the state of the art monitoring and what is the tradeoff. Finally, we conclude the paper in Section VI and present future work.

II. Related Work

A. Video Quality Estimation Methods

The perceived video quality can be investigated in subjective tests, where presented stimuli—such as impaired video sequences—are rated by subjects under controlled conditions. The grades of the scale are mapped for instance to numerical values from 1 (bad quality) to 5 (excellent) or 1 to 100, and the mean of the scores, the MOS value, is obtained for each test condition. The obtained rating expresses the subjective Quality of Experience (sQoE). The results of such surveys reflect the user's perception and thus have a high significance. However, due to different quality judgment of human observers, multiple subjects are required to participate in a subjective study [4]. According to [5], at least 15 observers should assess stimuli in order to gain significant results. Tests are conducted manually in a controlled environment which is time-consuming and costly. Thus, it should be used as base data for objective video quality algorithms which automatically predict the visual quality of a video clip. Objective video quality metrics can be classified into three categories by the required amount of reference information [6]: *Full-Reference* (FR) metrics are based on frame-by-frame comparison between a reference video and the video to be evaluated; *No-Reference* (NR) metrics have to make assumptions about the video content and distortions, e.g. by evaluating the blockiness of a frame, as a common artifact in block-based compression algorithms such as MPEG; *Reduced-Reference* (RR) metrics evaluate the test video based on a subset of features previously extracted from the reference video. Based on the complex nature of cognitive aspects and the human visual system, objective quality metrics do not capture its entire complexity and focus on aspects, which have been shown to correlate well with human perception in subjective tests. Typically publicly available full reference metrics can be used to compute the quality of a transmitted video clip, i.e., the Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Metric (SSIM), and Video Quality Metric (VQM). These mechanisms range in their complexity and their correlation with human perception.

B. Video Quality Monitoring in the Network

Different quality monitoring mechanisms of video over IP networks have been investigated in research. The most simple mechanism is to define a packet loss threshold for the IPTV service and assume the video quality as acceptable as long as the threshold is not exceeded. This technique does not take any video and content information into account. While a lost packet will produce a large error in regions with medium motion, it may produce no sizable error in regions with low motion. The mechanism introduced by Reibman et al. [7] focuses on no reference methods which estimate the video quality on network level and, if possible, on codec level. The estimation on codec level includes for instance spatio-temporal information and effects of error propagation. Tao et al. [8] propose a relative quality metric, rPSNR, which allows the estimation of the video quality against a quality benchmark provided by the network. The introduced system offers a lightweight video quality solution. Naccari et al. [9] introduce a no reference video quality monitoring solution which takes spatio-temporal error propagation as well as errors produced by spatial and temporal concealment into account. The results are mapped to SSIM and compared to results gained by computing the SSIM of the reference video and the distorted video. All these video quality monitoring mechanisms work on no reference or reduced reference metrics for estimating the video quality. A brief overview over current research questions within the area of IPTV monitoring can be found in [10].

III. Proposed Monitoring Solution

In this section, we first present the considered scenario for our proposed monitoring solution and detail the functionality of our approach.

A. Considered Scenario and Assumptions

The considered scenario for our proposed monitoring solution is a virtual network that has been created by combining the virtual resources of several physical infrastructure providers to host an IPTV streaming service (see Figure 1). A virtual network operator controls and manages the network and is responsible for a good service quality of customers. Hence, the virtual network operator deploys monitoring agents at critical locations in the network so that the monitoring can detect the location of possible performance problems, i.e. which physical domain is responsible. The agents either run directly on intermediate nodes or on dedicated monitoring nodes that receive mirrored traffic from intermediate nodes like routers or switches. With traffic or port mirroring, the data traffic is duplicated during the forwarding process and sent to preconfigured nodes which perform predefined traffic analysis or monitoring tasks. Due to emerging technologies like OpenFlow, this can even be achieved on a per flow and hence video stream basis. The IPTV service is connected to a cloud environment which is able to perform a fast SSIM-based video analysis on a per group of pictures basis. Thus, we apply a live SSIM-based video analysis to compute the distortion for loss scenarios where exactly one frame is lost. In addition, the inter-frame dependencies within a group of pictures are also extracted. This information is then distributed via a central monitoring database to the monitoring agents in the network. The agents monitor the multicast video streams and map monitored packet losses to the video quality and send this information to the central monitoring database. To track the transmitted frames, the monitoring agent can use deep packet inspection to discover the necessary information from the video frame header. However, this may constitute performance problems as a lot of streams may pass through the monitoring agent. Another possibility is to provide information via an additional shim header between transport and application headers. It includes the frame index and the number of packets per frame. The header is added at the edge close to or by the video streaming servers and is removed at the border to the customer domain. The agents then monitor the seen packet indexes in the shim header. If there is a gap in the frame index, the agent considers that frame as lost and calculates the service degradation at consumer side. This approach assumes that there is no packet reordering on one path so that we can infer lost packets from frame index gaps. To show the viability of our proposed monitoring solution, we have already implemented our solution in a testbed and a demonstration has been shown at the EuroView conference 2012 [11].

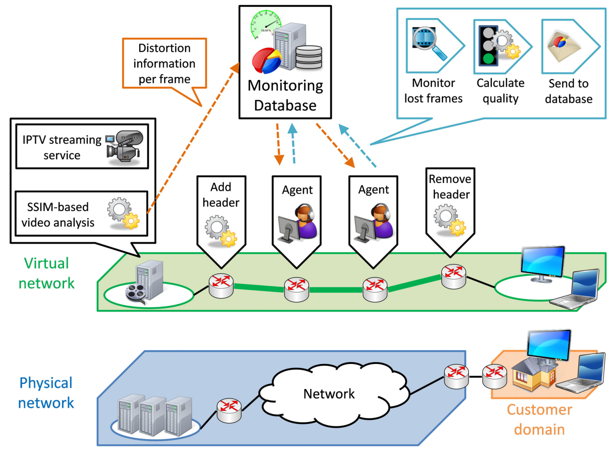


Fig. 1. Considered scenario and monitoring architecture.

B. Precomputation of Distortion

Our proposed monitoring solution uses detailed knowledge about the video to calculate how much influence a specific

Algorithm 1 Update process of d_{GOP}.

Input1: distortion of lost frame (d_{Frame})
Input2: current distortion per GOP (d_{GOP})
if lost frame not dependent on other frames **then**
  d_{GOP} += d_{Frame}
else
  if required frame is also lost **then**
    ignore distortion value for this frame
  else
    d_{GOP} += d_{Frame}
  end if
end if

lost packet and hence lost frame has on the service quality for consumers. We apply a cloud computing based live analysis of the streamed video and generate distortion information for loss scenarios where exactly one frame within a group of pictures is lost. The distortion values are computed according to the structural similarity (SSIM) [3] index and we define the distortion as the dissimilarity of two frames. Beneath the SSIM metric, several other methods, e.g. the video quality metric (VQM) are possible and we have chosen the SSIM metric as it offers a fast computation and good correlation. For each frame within a group of pictures, the video analysis generates a loss scenario where only this specific frame is dropped and the resulting distortion on all frames within that group is investigated. Therefore, we directly compare the undistorted image f_{Good} with the distorted image f_{Bad} via the SSIM method and hence obtain, how different the undistorted and distorted image are. The SSIM index yields values between *0* and *1* and the distortion value per frame d_{Frame} is defined according to Equation 1.

$$d_{Frame} = 1 - SSIM(f_{Good}, f_{Bad}) \tag{1}$$

The distortion value per single frame d_{Frame} hence has a maximum of one which means two completely different pictures. However, only I-frames are completely independent of other frames and constitute fixed pictures. All other frame types are dependent on other frames and if these frames are lost, the dependent frames cannot be decoded and must also be considered lost. Hence, a single frame can have a much higher distortion value in case a lot of other frames are dependent on this frame. To normalize the distortion per group d_{GOP}, we divide it by the number of frames per group. To get the dependencies between the frames in a group of pictures, we also investigate in the above emulated loss scenarios which other frames are also distorted in the currently considered group of pictures if a specific frame is lost. In total, the video analysis offers a high potential for parallel computing, i.e. processing the different loss scenarios on separate computing nodes within a computing cloud. Our current experience shows that depending on the degree of parallelization, this process is feasible within less than a second.

C. Calculation of Video Distortion

The distortion value is calculated per group of pictures and once the agent sees the next group of pictures in the stream, the old distortion value of the former group of pictures is sent to the monitoring database and the value is reset to 0 for the next group. For each lost frame per group then, the monitoring agent updates the distortion value d_{GOP} according to Algorithm 1. First, the monitoring agent checks whether the lost frame is dependent on other frames. If the lost frame is not dependent, the agent looks up the distortion value for the lost frame d_{Frame} and adds this value to the distortion value of the currently considered group of pictures (d_{GOP}) and the update process is finished. If in contrast the lost frame is dependent on other frames, the agent needs to check whether these frames are also lost. If the currently considered frame requires another frame which is also lost, the distortion of the current frame is already include and can be ignored. In this case, no update of the d_{GOP} value is required. If in contrast the required frame is not lost, the distortion of the currently considered lost frame is not yet included and hence, the distortion d_{Frame} is added to the d_{GOP} value.

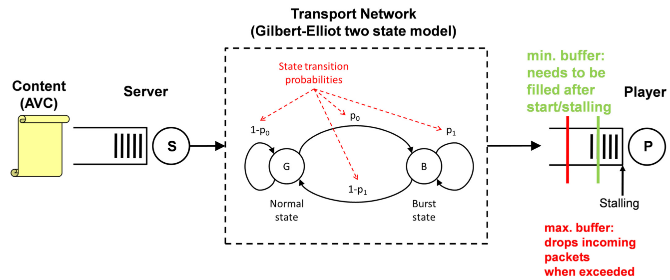


Fig. 2. Simulation model with Gilbert Elliot two state network model.

IV. Evaluation Setup

In this section, we describe the setup for the evaluation in Section V. We have implemented both monitoring solutions in the event-based simulation platform OMNeT++ [12] to quickly evaluate different loss scenarios. First, we describe the simulation model as well as the simulation setup. Then, we introduce the performance metric used to compare the two monitoring solutions.

A. Simulation Model and Setup

The implemented simulation model is depicted in Figure 2. A server module acts as streaming source and reads the video information from a video source file. This file contains for each frame the index, the type, the size, the number of packets, and the time stamp when the first packet of this frame should be sent. Subsequent packets of a frame are sent once the preceding packet has been written on the link. Hence, the link bandwidth at the server module influences the inter-packet time. For the simulation of different packet loss and burst scenarios in the network, we use the Gilbert-Elliot two state model [13], [14] which can be seen in the dashed box in Figure 2. This model is based on a Markov-Chain with two states that model different behavior of possible bottlenecks. The first state G is called normal state while the second state B is called burst state. The start state is state G and for each packet, a random number is drawn. In state G, Bernoulli random numbers with mean p_0 are drawn and in state B, Bernoulli random numbers with mean $(1 - p_1)$ are drawn. A random number of 0 means remaining in the current state and a random number of 1

TABLE I. INFLUENCE OF STATE TRANSITION PROBABILITIES ON BURSTINESS.

Packet loss	p_0	p_1	Burstiness
1.0 %	0.01	0.01	none
1.0 %	0.006	0.4	low
1.0 %	0.003	0.7	medium
1.0 %	0.001	0.9	high

TABLE II. QUALITY MAPPINGS.

Packet loss	Quality
$< pl_{threshold}$	good (1)
$\geq pl_{threshold}$	bad (0)

(a) Mapping: packet loss → quality.

Distortion	Quality
$[0, 0.01[$	good (1)
$[0.01, 0.05[$	good (1)
$[0.05, 0.12[$	good (1)
$[0.12, 0.5[$	bad (0)
$[0.5, 1.0]$	bad (0)

(b) Mapping: distortion → quality.

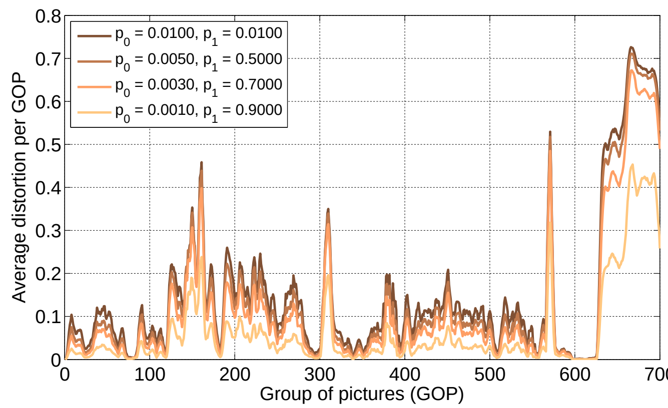


Fig. 3. Influence of Burstiness on Distortion-based monitoring solution.

means changing the state. If the model is currently in state G for a packet, nothing happens. However, if the model is in state B, the packet is dropped. The total packet loss as a function of p_0 and p_1 can be calculated as $p = \frac{p_0}{p_0 - p_1 + 1}$. Table I shows for a packet loss rate of 1 % the parameters p_0 and p_1 for different burst scenarios. If both parameters are equal, there are no bursts and there is a steady packet loss. For an increasing value of p_1, the burstiness also increases as long as the total packet loss remains the same. After the packets have traversed the network module, they arrive at a player module which simulates video playback and models the video sink. The player module also implements our proposed monitoring solution and calculates the distortion per group of pictures. We have investigated our proposed monitoring solution and the difference to the packet loss-based solution for different packet loss and burst scenarios. As video for the evaluation, we have used the SINTEL video [15] from the Durian open movie project in the 1080p version and with a group of picture size of 30. Each packet loss and burst scenario has been conducted 250 times in order to compute mean and confidence intervals.

B. Misclassification Rate per Group of Pictures

For the comparison of the proposed monitoring solution with the packet loss-based approach, we apply a mapping for both solutions to a common quality metric which rates the video quality of a group of pictures either *good* or *bad*. The packet loss-based monitoring approach maps the packet loss to the quality according to a threshold $pl_{threshold}$ which is shown in Table IIa. As long as the packet loss per group of pictures is below the threshold $pl_{threshold}$, the quality is good. If the packet loss is higher than the threshold $pl_{threshold}$, the quality is bad. For our proposed solution, the distortion is first mapped to the MOS value according to [3] and then to the video quality according to [10]. There the authors have shown via subjective tests for web services that 90 % of the users already accept a fair video quality (MOS 3). The resulting mapping from distortion to video quality can be seen in Table IIb. In the following, we assume the distortion-based monitoring as reference and define the misclassification rate per group of pictures as the difference between the monitored quality level of the distortion-based monitoring and the packet loss-based monitoring. *Underestimation of distortion* means that the packet loss-based monitoring rates a group of pictures good while the distortion-based monitoring rates the group of pictures bad. *Overestimation of distortion* means that the packet loss-based monitoring rates a group of pictures bad while the distortion-based monitoring rates the group of pictures good. The *total misclassification* is then the sum of the under- and overestimation rate.

V. EVALUATION

In the following, we present the evaluation of both monitoring solutions for different loss and burst scenarios. First, we present the sensitivity of our proposed monitoring solution regarding burstiness and packet loss. Second, we utilize the defined misclassification rate to show in which scenarios the simple packet loss-based monitoring is not suitable.

A. Influence of Different Packet Loss Scenarios

In Figure 3, we investigate the influence of different burst scenarios on the average distortion per group of pictures. The considered video for the evaluation has 700 groups of pictures in total. The different colored lines in the plot show the average distortion per group of pictures for different burst scenarios. In all scenarios, the total packet loss was set to 1 % and the dark brown line constitutes the no burst scenario. The bright orange line depicts the high burst scenario. The corresponding entries in the legend show the respective parameters of the Gilbert-Elliot model which have been used to generate the different scenarios. Considering the influence of the burst scenarios, it is apparent that the higher the burstiness in the network, the lower the average distortion per group of pictures. In the no and low burst scenarios, almost every group of pictures becomes distorted because there is a steady packet loss. If the bursts increase, the packet loss is not steady anymore and concentrates on fewer groups of pictures. For these few groups of pictures, the distortion is larger but not significantly larger due to the dependencies between the frames. If within a group of pictures all frames are dependent on the I-frame, it does not matter if only the I-frame is lost or if all frames of this group of pictures are lost, the distortion would be the same. Overall that is the reason why the average distortion per group of pictures is lower for higher burst scenarios. This result is in line with the results from other papers, e.g. [16]. To investigate the influence of the mean packet loss rate, we have plotted the average distortion per group of pictures against the mean packet loss rate in Figure 4. We see that there is a maximum average mean distortion per group of pictures of about *0.17*

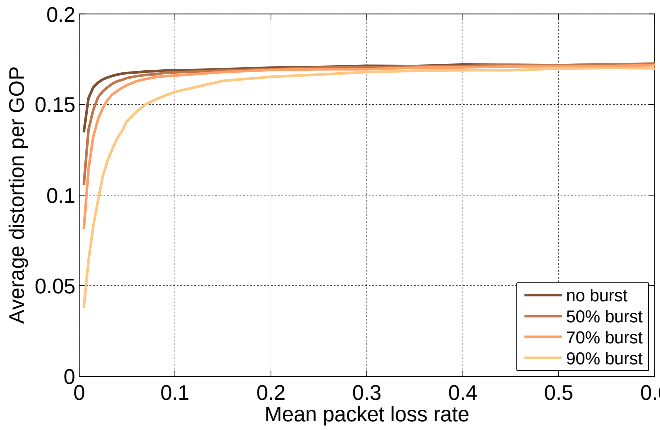


Fig. 4. Mean average distortion for different packet loss rates.

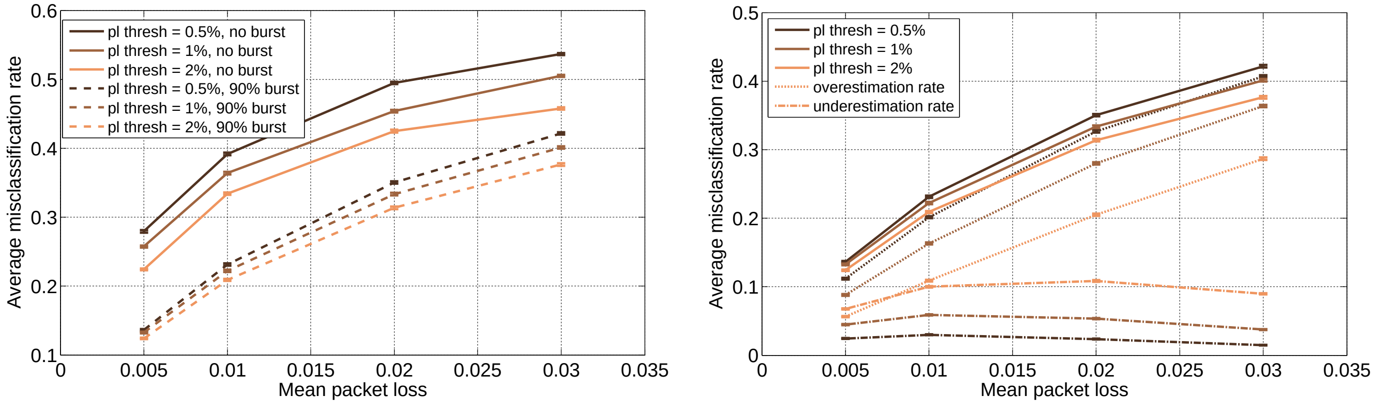
which is depending on the burst scenario reached after a certain mean packet loss. The higher the burstiness in the network, the later the maximum is reached. For the no burst scenario, the maximum is immediately reached once the mean packet loss is greater than 0. In the no burst scenario, there is a steady packet loss and increasing the mean packet loss rapidly leads to a larger fraction of affected groups of pictures than in the burst scenarios. There due to the packet loss burst, it takes a high mean packet loss until a similar fraction of groups of pictures is affected as in the no burst scenario.

B. Influence of Packet Loss Threshold on Misclassification

In the second part of the evaluation, we use the defined misclassification rate to compare our proposed monitoring solution with the packet loss-based monitoring solution for different packet loss and burst scenarios as well as for different packet loss thresholds. In Figure 5, we show the influence of the mean packet loss rate in the network on the average misclassification rate of groups of pictures. In Figure 5a, the misclassification rate for the no and high burst scenario as well as for different packet loss thresholds for the packet loss-based monitoring are shown. The solid lines denote the no burst scenario and the dashed lines denote the high burst scenario. By considering the no burst scenario, it can be seen that the misclassification rate of groups of pictures increases for an increasing mean packet loss rate. The high burst scenario behaves similar but the misclassification rate is lower in that case. The reason for the increase due to a higher packet loss rate is that the number of affected groups of pictures increases which leads to a higher chance of misclassification. This effect is reduced for the high burst scenarios as the number of affected groups of pictures decreases due to the occurring bursts. In Figure 5b, we separate the misclassification rate in over- and underestimation of distortion. The solid lines depict the total misclassification for the corresponding packet loss thresholds $pl_{threshold} = 0.5, 1.0, 2.0$ %. The dotted lines depict the overestimation rate and the dashed dotted lines depict the underestimation rate for the three different packet loss thresholds. For an increasing mean packet loss, the overestimation rate increases and constitutes a large fraction of the total average misclassification. The low packet loss thresholds in those cases lead to a high overestimation of distortion and indicate that the packet loss threshold is an important parameter which may negatively influence the accuracy. Concerning the underestimation rate, the higher mean packet loss has not much influence on the underestimation rate and first increases but then decreases again. For a higher mean packet loss, the peaks of the bursts gain intensity and more often exceed the packet loss threshold which leads to fewer classifications of good groups of pictures by the packet loss-based monitoring and a constant underestimation rate. As already mentioned, the packet loss threshold is an important parameter which may negatively influence the accuracy of the packet loss metric and in the following, we investigate the over- and underestimation rate for different packet loss rates and different packet loss thresholds. The x axes in Figures 6a and 6b show the packet loss threshold of the packet loss metric between 0 and 100 %. The different colored lines correspond to different mean packet loss rates while brighter lines correspond to higher mean packet loss rates. Considering the underestimation in Figure 6a, a packet loss threshold of 0 % leads to no underestimations as all groups of pictures are classified as bad. This however leads to the highest overestimation of distortion in Figure 6b. Increasing the packet loss threshold also increases the underestimation of distortion as more groups of pictures are falsely classified as good and decreases the overestimation as more groups of pictures are correctly classified as good. For a packet loss threshold of about 10 %, the underestimation rate has nearly reached its maximum and the overestimation rate is nearly 0 and negligible. Once a packet loss threshold of 50 % is reached, the overestimation of distortion is 0 and the underestimation has reached its maximum. For that threshold, all groups of pictures are classified as good and there are no groups of pictures classified as bad. These results show that there is no optimal threshold for the packet loss metric. The minimum misclassification is reached for a threshold larger than about 10 % but in that case, the underestimation of distortion constitutes a large fraction. From the service provider point of view, this means that possible problems are seen too late and the customers may already experience service degradations. Only by using our proposed monitoring metric, influences of packet loss on the service quality can be calculated with the required accuracy.

VI. Conclusion

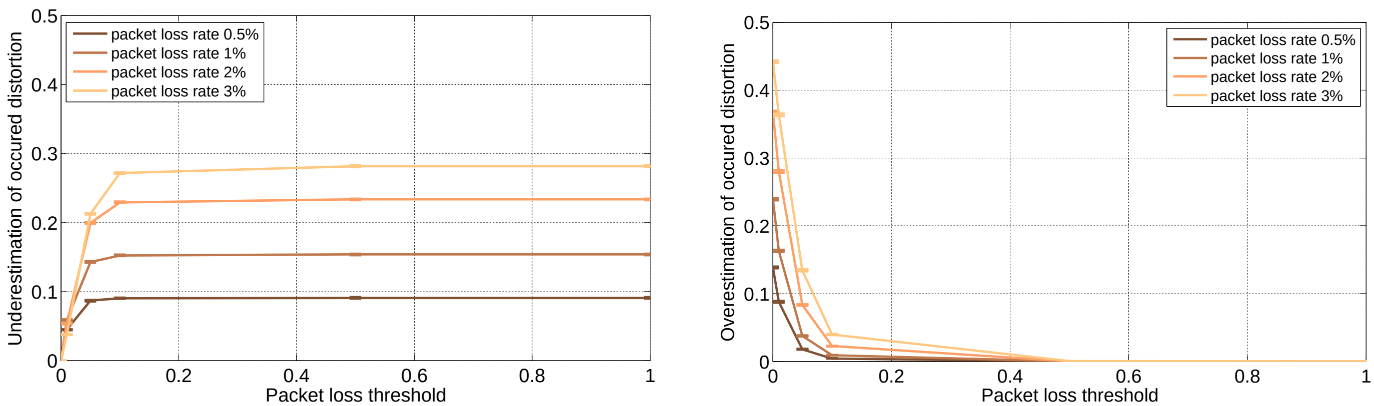
In this work, we proposed a monitoring solution for IP video streaming services which utilizes knowledge about the video content to predict the service quality under different loss and burst scenarios in the network. Our solution precomputes the distortion induced by losing frames using the full reference metric SSIM and the encoding dependencies between the frames. This information is continuously transmitted to monitoring agents distributed in the network. These agents calculate the video quality based on the forwarded video frames. To show the viability of our solution, we compared it with a typical approach based on packet loss thresholds. The results indicate that our solution outperforms the simple packet loss metric and is more suitable for video quality monitoring. Future work will focus on the comparison of the proposed solution with other monitoring approaches with respect to the trade-off between monitoring costs, scalability, and accuracy. This also includes subjective user surveys which can be used as one metric for the comparison, and also to improve the accuracy of the proposed video monitoring solution.



(a) Average misclassification for no and high burst scenario.

(b) Underestimation, overestimation, and misclassification for high burst scenario.

Fig. 5. Influence of mean packet loss on misclassification.



(a) Underestimation of distortion for high burst scenario.

(b) Overestimation of distortion for high burst scenario.

Fig. 6. Influence of packet loss threshold on over- and underestimation rates.

ACKNOWLEDGMENT

The authors would like to thank Prof. Tran-Gia for the support in this work. This work was funded by the Federal Ministry of Education and Research of the Federal Republic of Germany (support code 01 BK 0917, G-Lab COMCON).

REFERENCES

[1] C. S. Inc., "Cisco visual networking index: Forecast and methodology, 2011-2016," http://www.cisco.com/en/US/solutions/collateral/ns341/ns525/ns537/ns705/ns827/white_paper_c11-481360.pdf, June 2012.

[2] S. Meier, M. Barisch, A. Kirstädter, D. Schlosser, M. Duelli, M. Jarschel, T. Hoßfeld, K. Hoffmann, M. Hoffmann, W. Kellerer, A. Khan, D. Jurca, and K. Kozu, "Provisioning and Operation of Virtual Networks," *Electronic Communications of the EASST, Kommunikation in Verteilten Systemen 2011*, vol. 37, Mar 2011.

[3] Z. Wang, L. Lu, and A. C. Bovik, "Video quality assessment using structural distortion measurement," in *International Conference on Image Processing*, vol. 3, 2002, pp. 65–68.

[4] K. Seshadrinathan, R. Soundararajan, A. C. Bovik, and L. K. Cormack, "Study of subjective and objective quality assessment of video," *IEEE Transactions on Image Processing*, vol. 19, no. 6, pp. 1427–1441, Jun 2010. [Online]. Available: http://dx.doi.org/10.1109/TIP.2010.2042111

[5] ITU-R Rec. BT.500, "Recommendation 500-10: Methodology for the subjective assessment of the quality of television pictures," 2000.

[6] S. Winkler, "Video Quality and Beyond," in *Proc. European Signal Processing Conference*, 2007.

[7] A. Reibman, V. Vaishampayan, and Y. Sermadevi, "Quality monitoring of video over a packet network," *IEEE Transactions on Multimedia*, vol. 6, no. 2, Apr 2004.

[8] S. Tao, J. Apostopoloulos, and R. Guerin, "Real-Time Monitoring of Video Quality in IP Networks," *IEEE Transactions on Networking*, vol. 16, no. 6, Dec 2008.

[9] M. Naccari, M. Tagliasacchi, and S. Tubaro, "No-Reference Video Quality Monitoring for H.264/AVC Coded Video," *IEEE Transactions on Multimedia*, vol. 11, no. 5, Aug 2009.

[10] R. Schatz, T. Hoßfeld, L. Janowski, and S. Egger, "From Packets to People: Quality of Experience as New Measurement Challenge," in *Data Traffic Monitoring and Analysis: From measurement, classification and anomaly detection to Quality of experience*, M. M. Ernst Biersack, Christian Callegari, Ed. Springers Computer Communications and Networks series, 2012.

[11] T. Zinner, D. Klein, S. Meier, D. Wagner, M. Hoffmann, W. Kiess, V. Singorzan, and M. Schmid, "Dynamic Topology Adaptation enabled by Network Virtualization: A Use-Case for the Future Internet." 12th Wuerzburg Workshop on IP: ITG Workshop "Visions of Future Generation Networks" (EuroView2012), Jul 2012.

[12] A. Varga and R. Hornig, "An overview of the OMNeT++ simulation environment," in *International Conference on Simulation Tools and Techniques for Communications, Networks and Systems*, Mar 2008.

[13] E. N. Gilbert, "Capacity of a burst-noise channel," *Bell System Technical Journal*, vol. 39, pp. 1253–1265, Sep 1960.

[14] E. O. Elliott, "Estimates of Error Rates for Codes on Burst-Noise Channels," *Bell System Technical Journal*, vol. 42, pp. 1977–1997, Sep 1963.

[15] Blender Fountation, "Sintel: Durian open movie project," http://www.sintel.org/, Sep 2012.

[16] K. Yamagishi and T. Hayashi, "Parametric Packet-Layer Model for Monitoring Video Quality of IPTV Services," in *ICC '08. IEEE International Conference on Communications*, 2008, pp. 110–114.