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Considering User Behavior in the Quality of Experience Cycle: Towards Proactive QoE-Aware Traffic Management

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***Abstract*— The concept of Quality of Experience (QoE) of Internet services is widely recognized by service providers and network operators. They strive to deliver the best experience to their customers in order to increase revenues and avoid churn. Therefore, QoE is increasingly considered as an integral part of the reactive traffic management cycle of network operators. In addition, QoE also constitutes a cycle of its own, which includes user behavior and service requirements. This letter describes this QoE cycle, which is not widely taken into account yet, discusses the interactions of the two cycles, and derives implications toward an improved and proactive QoE-aware traffic management. A showcase on how network operators can obtain hints on the change of network requirements from detecting user behavior in encrypted video traffic is also presented.**

I. Introduction

INTERNET applications which are used by billions of users every day, are offered by application providers and delivered by network operators, which both strive to bring the best experience to their customers. This has become their major goal, as it was shown that a reduced user experience results in customer churn and a reduction of service revenues [1]. However, to monitor and optimize the user experience, which is typically implemented via control loops, application providers and network operators need concepts to quantify the experience and satisfaction of their customers.

Therefore, Quality of Service (QoS) was introduced, which is defined as "totality of characteristics of a telecommunications service that bear on its ability to satisfy stated and implied needs of the user of the service" [2]. Practically speaking, it quantifies the service delivery by network metrics, such as throughput, packet loss, delay, or jitter. However, for many services, QoS is not perfectly correlated with the user experience. With video streaming, for example, the user does not explicitly notice packet delays because they can be absorbed by the application buffer of the video player. Instead, he only perceives severe network issues, which propagate to the application layer, e.g., playback interruptions when the buffer is empty. Thus, the application behavior, which obviously depends on the underlying network, and its impact on user experience cannot be captured by pure QoS.

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To overcome these issues of QoS, the Quality of Experience (QoE) concept was developed, which focuses purely on the subjectively perceived quality. QoE is defined as "the degree of delight or annoyance of the user of an application or service. [...] In the context of communication services, QoE is influenced by service, content, network, device, application, and context of use" [3]. QoE depends highly on the considered Internet application and extensive subjective studies have to be conducted to understand all influence factors. Based on such studies, QoE factors–technical parameters on network and application layer with a high correlation to QoE–have been identified for popular services, and QoE models have been developed to map these factors to quality or acceptability scores. As these QoE factors can be monitored and influenced, this allows to consider QoE also in technical control loops. Most notable, the monitoring of QoE factors and estimation of user experience via QoE models is integrated in traffic management systems of network operators, which upgrades traffic management to QoE-aware traffic management.

While research in the networking domain has recognized that the network has a huge impact on QoE, e.g., [4], [5], this relationship between network and QoE is mostly considered to be like a one-way street. This is why most QoE-aware traffic management solutions follow a cycle with a reactive design: The QoE of a networked service is monitored, but only when QoE degradations are detected or imminent, traffic management actions are applied in the network to mitigate the QoE degradations. Thereby, however, it is neglected that the perceived QoE might influence the user behavior and lead to interactions with the service. These, in turn, might impact the network requirements and network traffic of that service, which again might affect the QoE. Thus, instead of a one-way street, QoE constitutes a cycle of its own.

This letter is the first to explicitly describe the QoE cycle and to elaborate its interactions with the cycle of QoE-aware traffic management. Moreover, the letter emphasizes the importance of considering and monitoring user behavior, which can provide valuable information to network operators. Implications are derived, which can be used to improve QoE-aware traffic management towards a more proactive design, i.e., to prepare the network in a timely manner for the future network requirements of the users' services. Such proactive traffic management might especially be desired when optimizing the QoE for multiple users with diverse services in heterogeneous networks, e.g., in the context of smart cities, where current and emerging services with different requirements are consumed by a huge amount of concurrent users, and can be delivered via a plethora of mobile and fixed networks.

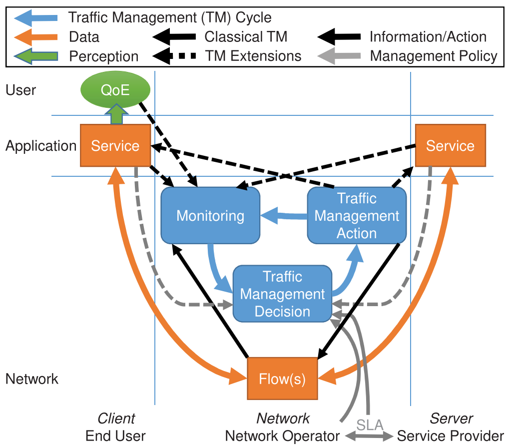

Fig. 1. QoE-aware traffic management cycle.

The remainder of the letter is structured as follows. Section II introduces the (reactive) QoE-aware traffic management cycle, while the QoE cycle is presented in Section III. The interactions between the two cycles are considered in Section IV. As an example, relevant user behavior during YouTube video streaming is identified, the potential for exploitation towards proactive QoE-aware traffic management is discussed, and a first result showing that user behavior can be predicted from encrypted traffic with high accuracy is presented. Finally, Section V concludes.

II. Quality-of-Experience-Aware Traffic Management

The initial goal of the implementation of traffic management by network operators was to meet service-level agreements (SLAs) for data transmissions and to reduce their costs by sophisticated utilization of the network resources. In early stages, pure network traffic management mainly focused on the efficient transmission of packets and flows. Since the rise of the QoE concept, they transitioned to QoE-aware traffic management, which additionally aims to improve the QoE of Internet applications to reach a high user experience. This includes cross-layer traffic management, which utilizes information from different layers (e.g., application-layer information) for the traffic management process, and collaborative traffic management, which is based on the communication and information exchange between different stakeholders (e.g., exposure of client-side information to the network) to manage the interplay of services and the network.

Different approaches for QoE-aware traffic management approaches in wireless networks were surveyed in [6]. In contrast, [7] only focused on mechanisms for improving the QoE of video streaming. Also [8] surveyed mechanisms for video streaming, but additionally differentiated between pure network traffic management solutions, and cross-layer and collaborative mechanisms.

The QoE-aware traffic management process can typically be described by a management cycle as depicted in Figure 1 [8]. It shows an Internet service (orange) seen from different layers (vertical separation) and stakeholders (horizontal separation). The solid lines indicate classical network traffic management and the dashed lines show possible extensions by cross-layer and collaborative traffic management. The traditional QoE-aware traffic management cycle is shown in blue, and is typically implemented in the network (solid lines). First, the current situation is monitored, e.g., in terms of QoS parameters measured on the network elements or QoE parameters, which were extracted from the network traffic. The monitored data is collected, processed, and aggregated to performance metrics, such as individual QoE factors or estimated QoE scores. They are compared to target values, which can be predefined by the network operators, derived from SLAs, or (dynamically) specified by the application or depending on the service requirements. If the performance metrics and the targets diverge, a traffic management action has to be decided. Such actions include network mechanisms (e.g., routing, prioritization, bandwidth shaping, offloading, caching), which are put into effect by changing the settings of network elements specifying how to handle the respective flows. Afterwards, the cycle restarts and the monitoring of the performance metrics continues. The classical network traffic management can be extended (dashed lines) by cross-layer and collaborative approaches, which allow to also monitor QoE on the application layer, e.g., within the client application, and user layer, e.g., through quality feedback within or after a session. This QoE information can then be signaled by the client. Moreover, service characteristics can be considered for traffic management decisions or even altered by traffic management actions, e.g., by sending requests to applications to change their network demands.

III. Quality of Experience Cycle

For reactive QoE-aware traffic management systems, it suffices to consider the relationship between network and QoE like a "one-way street", i.e., the network influences the service performance and presentation, and thus, the QoE. However, when designing proactive QoE-aware traffic management systems, the reaction of the user to his experience, i.e., the user behavior, with an Internet application has to be understood and considered. Obviously, user behavior can be influenced by the QoE, and it can influence the service and the network traffic itself, e.g., by interactions with the application client. Thus, by additionally taking into account the user behavior, the above mentioned "one-way street" can be extended to a QoE cycle.

The inclusion of user behavior in the QoE cycle is backed by related works, such as [9], which recognized that user behavior aspects were not well integrated in QoE research. They presented a comprehensive framework for modeling both QoE and user behavior. Therefore, they follow a technical perspective and introduce a user state model, which acts as an intermediate and can both influence and be influenced by QoE and user behavior. In contrast, [10] is based on a strong psychological background, and presented a conceptual model that relates the quality formation process to user behavior in multimedia consumption. Thereby, user behavior, e.g., interactions with the application when facing QoE degradations, is a result of (post-)conscious or affective processes that follow on the perception and the quality formation, and can affect the perceived stimulus. Reference [11] observed that QoE can be inferred from monitoring user behavior, while [12] showed

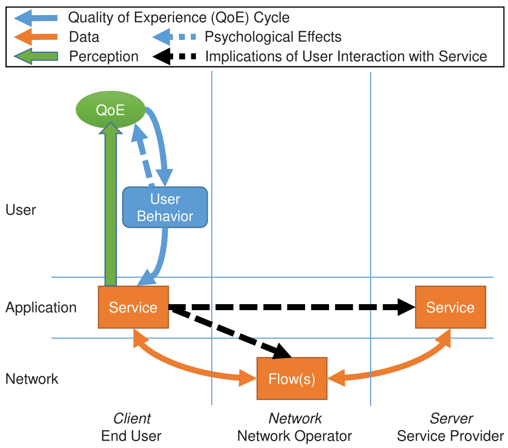

Fig. 2. Quality of Experience cycle.

that QoE could be altered by user behavior following the consistency principle or cognitive dissonance.

The QoE cycle is depicted in Figure 2, which shows again an Internet service (orange) seen from different layers (vertical separation) and stakeholders (horizontal separation), similar to Figure 1. However, as QoE is strictly subjective, this time, the figure is zoomed in on the user domain. The service is delivered through the network and is presented to the user through the client application. It is well understood that the service performance and presentation is affected by the network, e.g., [4], [5], and influences the QoE of the user (green arrow). The extension of this simple relationship to the QoE cycle is depicted in solid blue arrows, and indicates the impact of QoE on the user behavior. For example, [13] showed that QoE degradations in video streaming from stalling lead to shorter service usage time and [1] reported on customer churn on bad web site performance. As mentioned above, it should not be neglected that there are psychological effects also directly from user behavior towards QoE, which are depicted by the dashed blue arrow. Reference [14] found that video impairments can trigger user interactions, such as pausing the streaming and reducing the screen size. Such interactions influence the service, which might have implications on the service characteristics or the network traffic (dashed black arrows). For example, abandoning the service reduces the overall network traffic, or resizing the screen in case of video streaming might cause the service to change the streamed video bit rate, and thus, alters the network requirements of the service. Thus, the extended QoE cycle includes also the flows in the network, which is especially relevant for monitoring and predicting user behavior as well as the resulting network traffic and requirements in proactive QoE-aware traffic management.

IV. Interactions of the Two Cycles–Towards Proactive QoE-Aware Traffic Management

A classical approach to QoE-aware traffic management is to observe degradations in the network conditions, which can negatively affect the QoE. For example, for video streaming, a too restrictive bandwidth shaping or reductions of network throughput due to bandwidth fluctuations might result in increased initial delay and stalling, which have a negative impact on the QoE [5]. Although application traffic is mostly end-to-end encrypted these days, these degradations can already be monitored in the network with high accuracy with the help of machine-learning approaches, e.g., [15]–[17], and QoE-aware traffic management can react to mitigate the QoE degradation and improve the QoE.

This work proposes that, instead of only reacting when a QoE degradation has already happened, QoE-aware traffic management has to become proactive in that it recognizes or even predicts changing network conditions and requirements. This allows to adjust the network configuration in time to completely avoid that the user has to experience QoE degradations. Thereby, it is not sufficient to only monitor the service in the network or the application, or ask feedback from the user. Instead, as described above, user actions must not be neglected because they can provide valuable information for QoE monitoring and for proactive QoE-aware traffic management. In the following, these relevant user actions will be identified for YouTube video streaming, which is one of the most popular and most demanding services on the Internet, and it is discussed how they can be exploited for proactive QoE-aware traffic management and for QoE monitoring.

Several user actions indicate that a downloading burst of video data (buffer filling phase) is about to start or continue, namely, start of playback or resuming after a pause, scrubbing to another playback position (if outside of the buffered playtime range), skipping of an advertisement, or switching to another video. In contrast, a (temporary) end of the downloading can be expected after the user triggered a pause of the playback or aborted the video playback. While these user actions change the overall network load in terms of flows, also the required bandwidth of the streaming flows can be changed by the user, and thus, has to be reevaluated by the network operator, when he manually changes the video quality or switches to another video. Moreover, a user can influence the frequency of download bursts by altering the playback speed. This shows that detecting user actions brings valuable information to network operators about current and future characteristics and requirements of the streaming traffic, which can be used to adjust the network accordingly, and thus, avoid QoE degredations.

User actions can also provide valuable information about the subjectively perceived quality and satisfaction with the streaming service, which can be used to improve the QoE monitoring. There are some user actions which potentially indicate bad QoE, such as when the user triggers a pause, changes the video quality, switches to another video, or even aborts the video. The last two user actions could also hint to a lack of interest, which could also be the cause for changing the playback speed or scrubbing forward. In contrast, if the user skips an advertisement, resumes the playback, or scrubs backward to a previous playback position could be signs of his interest in the video content. Finally, detecting a manually triggered quality change or the change of display size due to smartphone rotation or toggling of fullscreen mode is crucial for correctly estimating the visual quality of the video stream. Apart from this momentary QoE indicators, also long-term QoE information can be derived, e.g., service usage metrics can be obtained from frequency of playback starts. Note that only few letters have addressed QoE evaluation based on user

TABLE I
PREDICTION RESULTS FOR VIDEO SWITCH DETECTION

	Predicted class		Prediction metrics		
↓ **Actual class**	No switch	Switch	Precision	Recall	F1
No switch	908,206	24,872	0.9733	1.0000	0.9865
Switch	12	433	0.9730	0.0171	0.0336
Weighted avg.			0.9733	0.9995	0.9860

behavior, e.g., [14], [18], and that correctly labeling the root causes behind some or all of the user actions is still an open issue, especially as individual users might act differently in different situations. Nevertheless, if these causes could be accurately identified, a lot of valuable QoE information could be available from monitoring user actions.

Finally, as a showcase, one of the above discussed user actions shall be detected from encrypted traffic, namely, the switch to another video during the streaming. Detecting video switches allows to prepare for the start of a burst download and hints at changing network requirements in terms of video bitrate. This gives valuable information for proactive QoE-aware traffic management. For example, knowing that the video has changed, network operators could reevaluate their video bitrate estimation in order to allocate sufficient bandwidth and avoid stalling of the streaming. The setup of [17] and a dataset of 11,942 streamed and monitored YouTube sessions is used, out of which 2,208 contain a video switch by clicking on a link to another video on the video page. The encrypted network traffic was split into time slots of 1 second and 208 constant memory features were computed based on statistics about packet size and inter-arrival time. All technical details can be found in [17]. 80% of the video sessions are used as training set with 3,739,196 time slots, out of which 1,763 (0.05%) contained a video switch. After bootstrapping, a random forest model with 10 trees was trained, and it predicted for the remaining 933,523 time slots of the 20% test sessions whether a video switch happened or not. The results are presented in Table I. The model is able to correctly predict 97.33% of the time slots, and reaches a precision of 97.30% and a recall of 1.71% for predicting video switches. Thus, the model sometimes wrongly detects a video switch in time slots without a video switch, but it rarely misses a video switch. This allows network operators to dramatically reduce the monitoring overhead by focusing on the 2.71% of the time slots (true and false positives) for which a video switch is potentially triggered. Clearly, this model suffers from the very unbalanced classes, but it will improve with more balanced training data. Still, the showcase demonstrates that video switches, and thus, potentially also other relevant user behavior, can be inferred from encrypted traffic and can provide valuable information for proactive QoE-aware traffic management.

V. CONCLUSION

This letter described how the common understanding of the relationship between network and QoE can be extended to a QoE cycle by considering the user behavior. Understanding the QoE cycle allows to comprehend the interplay between network and users, which has several implications and gives possibilities to advance reactive QoE-aware traffic management towards proactive QoE-aware traffic management. Relevant user actions for video streaming were discussed and a simple showcase was presented how a user-triggered video switch could be predicted from encrypted YouTube traffic using machine learning. Monitoring this user action gives information about the start of a download burst and hints to the change of network requirements, which is valuable information for QoE-aware traffic management. It allows to proactively configure the network to prevent QoE degradations, e.g., by reevaluating the video bitrate and allocate sufficient bandwidth to avoid stalling. In future works, the used prediction model will be improved, accurate models for the other relevant user actions in video streaming will be developed, and the valuable information derived from monitoring user behavior will be included into proactive QoE-aware traffic management solutions.

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