Online Appendix to paper: A Survey of Emerging Concepts and Challenges for QoE Management of Multimedia Services

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A DIFFERENT QOE OPTIMIZATION OBJECTIVES AND METRICS BEYOND MOS

Following a discussion of different challenges and solutions for managing QoE of multimedia services, we briefly discuss different metrics and optimization objectives considered in driving QoE management and optimization decisions.

A.1 Optimization objectives

The overall goal of QoE management may be related to optimizing end-user QoE (end-users' perspective), while making efficient (current and future) use of network/system resources and maintaining a satisfied customer base (providers' perspective) [1, 4]. While application-management mechanisms generally focus on a single user and exert control on the application level, network management mechanisms generally consider domain wide optimization and resource allocation problems. Joseph and de Veciana [13] combine these notions and address the problem of jointly optimizing network resource allocation and video quality for DASH-based video delivery, with the objective being to fairly maximize end users' QoE in light of tradeoffs between mean quality, temporal variability in quality, and fairness.

The objective of QoE-driven resource allocation has commonly been formulated as being to maximize users' aggregated sum of utilities [15], exploiting Network Utility Maximization (NUM) methods and mechanisms [5]. From a service provider's point of view, bounds imposed on the corresponding costs of optimizing QoE limit the solution space; e.g., a cost threshold will determine the maximum available bandwidth of the system (or the number of servers). Thus, given certain bounds, the objective is to distribute available resources in a QoE-optimal way.

Given a system with multiple simultaneous users accessing shared resources, the aforementioned objective may be formulated in different ways, such as maximizing the average QoE, or maximizing the percentage of users rating above a certain threshold. The literature further advocates the

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need to consider ensuring QoE fairness among users [6, 14]. Different approaches to solving this multi-objective QoE optimization problem may be considered, such as [8]:

- A *two-step* approach whereby a solution is found maximizing average quality, followed by a second step to solve for maximum fairness while maintaining the previously determined average quality level.
- A *utility approach* where the optimization goals (such as cost minimization, average quality maximization, fairness maximization, energy consumption minimization) are combined to derive a utility function.

A general QoE fairness index F has been recently defined by Hoßfeld *et al.* [10], which fulfills some desirable properties that are violated by the commonly cited Jain's index [12] or coefficient of variation. The index F may be applied in designing QoE management mechanisms and system optimization, or when benchmarking different resource management techniques.

Finally, going beyond typical NUM methods such that multiple types of resources are considered, and utility functions are dynamically learned from real datasets, Bao *et al.* [3] propose a data-driven resource allocation framework for improving user experience. Their closed-loop approach utilizes a trained logistic regression classifier to predict user experience, and then uses this likelihood as an objective function when computing the optimal resource allocation across multiple users. User experience is then subsequently evaluated given the allocated resources and used to adjust the trained model as necessary.

A.2 Minimizing energy consumption

In the context of mobile services, an important objective to consider when optimizing QoE is that of minimizing energy consumption [11]. The literature suggests various proposals to take into account the power consumption of mobile devices while receiving, decoding and presenting multimedia content [17]. Several algorithms [2] utilize the playback buffer information to change the wireless state of the device, e.g., continuous active vs. power saving mode. Tao *et al.* [16] also consider energy efficiency and QoE by utilizing context information in terms of knowledge of a look-ahead window. A survey on energy efficient multimedia streaming to mobile devices is provided in [7].

A.3 QoE Metrics beyond MOS in QoE Management

Typically, QoE management mechanisms rely on QoE models that estimate the MOS for a given set of input parameters. Recent work has emphasized the need to consider QoE metrics beyond MOS and their relevance for QoE management so as to integrate different stakeholder perspectives. In a subjective study, the MOS is simply the average over all user ratings for a particular test condition or stimuli. While the user ratings are a random variable describing the user (rating) diversity [9], the MOS provides a simple scalar value for QoE. Obviously, the mean value of a random variable has several limitations. The MOS averages out the user diversity and does not provide a way to address variations between users. In that sense, the MOS depicts a (non-existent) "average user" of a system.

For QoE management, service providers may target to have at least 95% of their users satisfied with a certain service quality. This may be expressed by quantiles or θ-acceptability [9]. The latter is defined as the probability that the opinion score is above a certain threshold. Quantiles indicate the rating of a fraction of the most satisfied (or dissatisfied) users. To quantify the user diversity, standard deviations of opinion scores (SOS) are appropriate. A discussion on those QoE metrics can be found in [9], while Matlab scripts for computing the QoE metrics for given data sets are available as supplementary material to [9] as well as in GitHub[1].

[1]https://github.com/hossfeld

Which QoE metric to use depends on what the operator considers to be most important, e.g., the average user, the most critical ones, the majority that are sensitive to changes in the delivered quality, etc. Assuming a user i is given resources x_i, the question of "what is that users' QoE?" amounts to the following: assuming this is an average user, QoE may be estimated using the MOS metric. On the other hand, assuming a"critical" user, the 10%-quantile could be used. We present below different QoE metrics and their meaning when using them in the context of QoE management. Moreover, in [8], Hoßfeld *et al.* address the implications of considering these different metrics on the QoE management solution/outcome (e.g., resource allocation decision).

QoE metrics and their interpretation for QoE management [9].

- MOS: average user rating for one test condition
- SOS: user diversity for that test condition
- 10%-quantile: user rating of 10% most critical or dissatisfied users
- 90%-quantile: user rating of 10% most satisfied users
- θ-acceptability: ratio of users rating equal or larger than θ
- GoB: ratio of users rating good or better ($\theta = 4$)
- PoW: ratio of users rating poor or worse
- Probability distribution: complete information about the randomness in the opinion score caused by user rating diversity

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