WAITING TIMES IN QUALITY OF EXPERIENCE FOR WEB BASED SERVICES

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Abstract

A considerable share of applications such as web or e-mail browsing, online picture viewing and file downloads imply waiting times for their users, which is due to the turn-taking of information requests by the user and correspoding response times until each request is fulfilled. Thus, end-user quality perception in the context of interactive data services is dominated by waiting times; the longer the latter, the less satisfied the user becomes. As opposed to heavily researched multimedia experience, perception of waiting times is still not strongly explored in the context of Quality of Experience (QoE). This tutorial will contribute to closing this gap. In its first part, it addresses perception principles and discusses their applicability towards fundamental relationships between waiting times and resulting QoE. It then investigates to which extent the same relationships can also be used to describe QoE for more complex services such as web browsing. Finally, it discusses applications where waiting times determine QoE, amongst other factors. For example, the past shift from UDP media streaming to TCP media streaming (e.g. youtube.com) has extended the relevance of waiting times also to the domain of online video services. In particular, user-perceived quality suffers from initial delays when applications are launched, as well as from freezes during the delivery of the stream. These aspects, which have to be traded against each other to some extent, will be discussed mainly for HTTP video streaming in the last part of this tutorial.

***Index Terms*—** Waiting Time Perception, Web QoE, YouTube Video Streaming, Stalling, Initial Delay, QoE, Subjective Tests

Disclaimer

The authors want to point out that this is an invited paper which is based on previous publications by the authors [12,21,23,38,48] and partly reuses contents in terms of figures and text passages. The original figures and publications are clearly referenced and provide the tutorial audience with links to further reading.

The tutorial is aimed at researchers interested in the impact of waiting times and delays on QoE, in particular, for web-based applications such as web browsing and video streaming. Since the content of the tutorial is on fundamental relationships known from psychology which are applied (in theory and practice) to web-based services, all level of researchers are welcome: PhD students with basic background on QoE as well as QoE experts. The structure of the tutorial is reflected by the table of contents of this paper.

1. INTRODUCTION

Time is non-recurring. Other than money and goods, it cannot be reproduced, extended or multiplied. In general, people do not like to wait unnecessarily since time spent on unnecessary or unproductive matters is considered to be lost. This particularly applies to waiting times when time cannot used it for other purposes.

Reference [31] puts an experience of early World Wide Web (WWW) adopters in the middle of the 1990s in a nutshell by asking "Tired of having to make coffee while you wait for a home page to download?". The page reminds of the growth of waiting times in Europe during the afternoon when the American users became active; users associated WWW with "World Wide Wait". In the meantime, the early-afternoon problem lost importance due to massive installations of server and network capacities. Today, we are facing other slowpokes such as overloaded terminals and access networks, or ineffective service chains. As interactive applications dominate the computer world, with very different activity grades ranging from initiating a video transfer in a browser via web-based work processes to online gaming, associated waiting times on quite different timescales (for the video start; for the web form to become updated; for the game to react to one's input) have become daily business and bones of contention for users.

Technically speaking, service usage on the WWW (or short Web) is characterized by a request – response scheme where the user issues a request for a search result, a web page, a file download, a video and so forth. Typically, the response of these requests is not instant but rather delayed to a certain extent (influenced by the type of request and the type of desired response). As a result, user-perceived quality is largely dominated by these response times or waiting times, respectively. Figure 1 provides an illustration of waiting time for web-based services.

The importance of limited waiting times for successful e-commerce was investigated already in the early days of the Web. Reference [62] points out an 8 s-limit of page download time to be kept in order to avoid user churn. In the study [7], users were given tasks in a web-shop with deliberate additional delays. Most interesting are some citations of user reactions, such as "If it's slow, I won't give my credit card number"; "This is the way the consumer sees the company...it should look good, it should be fast"; "As long as you see things coming up it's not nearly as bad as just sitting there waiting and again you don't know whether you're stuck"; "You get a bit spoiled. I guess once you're used to the quickness, then you want it all the time". Obviously, waiting times affect user trust into the sys-

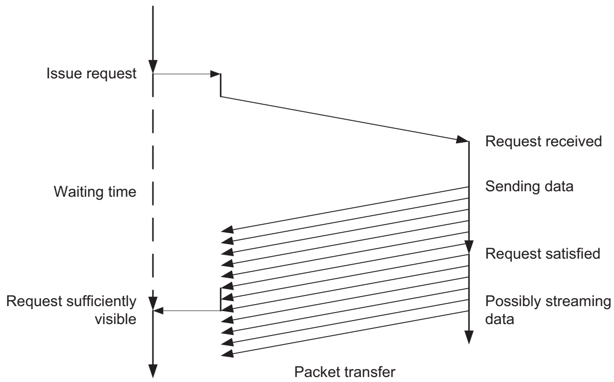

Fig. 1. Illustration of Waiting Time (modified from [38]).

tem and the company behind it, and can easily become showstoppers once money gets involved. Furthermore, decreases in waiting times increase user expectations on performance; based on the knowledge and experience of how quick responses could be given, subsequently growing waiting times are perceived as particularly disturbing.

Research on QoE has so far been dominated by multimedia services. However, it may be observed that early literature even refers to web experience. For instance, reference [32] investigates the relationship between (limited) access speed and the share of user-broken sessions, which are clear signals that users lost patience. Also in the study [52], users were given the opportunity to break the download of a picture once they ran out of patience, which typically happened after 10 to 20 s. As increasingly many videos are offered via the web, having to *wait for a video to start* has become a widely-known phenomenon. Furthermore, the increased use of TCP as transport protocol and the corresponding transformation of packet losses and reorderings into delays frequently make users *wait for a frozen video to resume* and turn attention from well-researched spatial issues (i.e. artefacts within the video pictures) to temporal issues. Obviously, user patience is challenged by waiting times before and during video consumption, and too long and/or frequent waiting times imply risk for user churn as for any other interactive service. For telecom operators, the special character of web-based interactive services changes their quality paradigm from "What *distortions* are tolerable to ensure a certain degree of user satisfaction" towards "Which *waiting times* are sufficient to ensure a certain degree of user satisfaction".

On this background, the paper sets out to contribute to the understanding of temporal QoE issues, in particular of the impact of waiting times on QoE. Its remainder is structured as follows. In Section 2 we review related work from psychology on human time perception. Section 3 describes a set of studies which have been conducted in order to prove that for simple interactive data services, time perception principles from psychology are also applicable to explaining the logarithmic relationship between waiting times and resulting user satisfaction ratings. In addition it is discussed whether the same relationship also holds true for more complex services such as web browsing. By doing so, we identify several difficulties on the technical as well as the user level which increase the complexity of quantifying web browsing QoE considerable. Section 4 addresses waiting times both before and during video delivery. Finally, Section 5 concludes the paper with a brief summary.

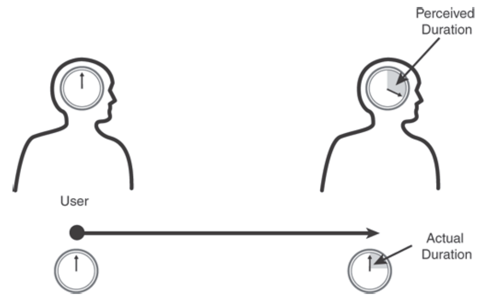

Fig. 2. Perceived duration vs. objective duration from [51].

2. TIME PERCEPTION IN PSYCHOLOGY

Work on human time perception covers a wide range of temporal perspectives on human behavior (see [20] for a comprehensive review). This includes time estimation, perception of durations, the underlying timing systems in the human brain etc. The aim of this tutorial is not to go into the whole deepness of the psychological literature but rather focus on the general terminology and relationships between human time perception and psychophysical principles[1]. By reviewing the related work on human time perception one encounters several different notions about the subjectively perceived time used by the subject for making his judgment. Therefore, we want to point out that the terms perceived, internal, subjective, psychological, and apparent duration (time) are used interchangeably; generally speaking, they refer to the temporal value(cf. [1]).

As in the domain of multimedia quality evaluation different modalities have to be considered, researchers should be aware of differences between modalities regarding time perception. By its nature, time can not be a direct stimuli but is a certain duration between electrial stimuli signals of the nervous system. This requires the transformation from physical signals into a electrical signals in the nervous system via a sensory organ. Due to the different (temporal) properties of different sensory organs the temporal resolution differs for stimuli of different modalities. Auditory stimuli are more precisely processed on a temporal level compared to visual or tactile stimuli [19]. A further difference is the fact, that auditory marked intervals are perceived longer as visually marked ones [17, 36]. Another characteristic of temporal stimuli is the effect that there are instances in which the second of two intervals is perceived as being much shorter than the first one, an effect known as the time-shrinking illusion [4]. These differences and characteristics of temporal stimuli have to be considered in the relation between waiting times and QoE.

In human time perception it is acknowledged that (subjective) perception of a duration should never be assumed to be accurate and true to the actual duration[2]. Whereas actual duration reflects objective time, perceived duration reflects subjective psychological time, which is susceptible to varying degrees of distortion. When users do gauge durations, they are more likely to rely on mental estimations rather than objective measurements [1, 20, 51] as depicted in Figure 2.

In the context of interactive applications system response times do not only contribute to the user's perceived quality of the system

[1]An exhaustive survey on the four laws of psychophysics can be found in [64].

[2]This is similar to difference between subjectively perceived quality and objectively measured quality (QoS).

but also add to the felt interactive nature of the system. [38] summarizes three important limits for subjective response times (i.e. waiting times) stemming from [43] and their relation towards perceived interactivity:

- 0.1 s is about the limit for having the user feel that the system is reacting instantaneously.
- 1.0 s is about the limit for the user's flow of thought to stay uninterrupted, even though the user will notice the delay.
- 10 s is about the limit for keeping the user's attention focused on the dialogue.

However, user satisfaction or user perceived quality is not automatically linked with these times as there are also other influencing factors to be considered such as service or application, expectations etc. For analyzing user satisfaction based on perceived duration [51] states that this is only meaningful when the perceived duration is compared to a tolerance threshold. If the perceived duration is shorter than the tolerance threshold, the user interprets that as fast and decent. Conversely, if the duration is perceived as longer than the tolerance threshold, the user interprets the duration as slow and insufficient. The value of this tolerance threshold is influenced by the context, personal factors, past experiences etc. (cf. [51]). Putting that into the QoE context it is obvious that this is congruent with the formation of subjectively perceived quality as described by [30, 47]. An example for the context influence of the duration threshold reads as follows [51]: *A ten-minute wait for a person who is already 15 minutes late for an important meeting is excruciating. The same ten-minute wait for a person who has already waited three days for a package to arrive is trivial.* This also exemplifies nicely the importance of the relation between stimuli and stimuli change for user satisfaction with a service and bridges to the principles of psychophysics and human perception [14, 57]

Initial work on psychophysical principles in human time perception has been conducted by [13] already in 1975, where a relationship between the magnitude of the error of time estimations and the duration of the sample length to be estimated has been identified and attributed to Steven's Power Law [54]. Successive work by [1] extended these results and added other models including the Weber-Fechner-law while [18, 33] set out to identify the minimal achievable error for time estimation based on the aforementioned models. They came to the conclusion that the relationship between estimation error and stimuli length is constant, which is essentially a version of Weber's law where the estimation error (termed Weber Fraction) is equivalent to the just noticeable difference already discussed above. Extension of these results to time related problems in other disciplines such as medicine [55] or consumer behavior research [3, 63] has proven that these relations can be successfully transferred from psychological lab studies to real world problems. Of particular interest to our problem is the work of [3], which shows that for the subjective evaluation of waiting times on a linear scale a logarithmic relationship does apply. Within the remainder of this tutorial paper we will additionally focus on this logarithmic relationship between waiting time and QoE.

3. SURFING VS. WAITING: WEB QOE

In general, the term Web QoE stands for the Quality of Experience of interactive services that are based on the HTTP protocol and are accessed via a browser [22]. The most prominent application examples of this category are surfing the web, downloading files (e.g. mp3 songs) and handling e-mails. Since from a user perspective the interaction with such applications is based on the same WIMP[3] paradigm known from traditional GUI-based desktop multimedia applications, similar principles of time perception and QoE apply to both categories [16, 53].

3.1. QoE of Web Browsing

As concerns web browsing it has been widely recognized that in contrast to the domains of audio and video quality, where psychoacoustic and psycho-visual phenomena are dominant, end-user waiting time is the key determinant of QoE [6, 41, 42]: the longer users have to wait for the web page to arrive (or transactions to complete), the more dissatisfied they tend become with the service.

3.1.1. From Pages to Sessions

From a technical perspective, a web page is an HTML (Hyper Text Markup Language) text document with references to other objects embedded in it such as images, scripts, etc. While HTTP Hyper Text Transfer Protocol) constitutes the messaging protocol of the Web, the HTML describes the content and allows content providers to connect other web pages through hyperlinks. Typically, users access other pages or new data by clicking on links, submitting forms. Within this basic paradigm, each clicked link (or submitted form) results in loading a new web page in response to the respective HTTP request issued by the user, resulting in a new *page view* whose QoE is characterized by the the time the new content takes to load and render in the browser. Furthermore, the surfing user typically clicks through several pages belonging to a certain web site and of course also occasionally changes sites as well. In this respect, user's web *session* can be characterized by a series of page view events and the related timings of the stream of interactions (see Figure 3b).

3.1.2. From Request-Response to Flow Experience

The speed and fluidity of the browsing experience has been shown to depend on a number of factors, particularly on QoS (Quality of Service) parameters of the underlying network. In particular, large packet delay or low bandwidth are well known to cause long loading times of objects and thus unacceptable completion times of page views (cf. [2, 6, 8]). In this respect, the time elapsed between the URL-request (e.g. caused by a click on a link) and the finished rendering of the Web page, referred to as page load time (PLT), is a key performance metric (see Figure 3b). Another relevant metric is the duration from request submission until the rendering of the new page starts, i.e. when the user receives the first visual sign of progress [10, 45]. In dedicated lab studies, these page view centric metrics have been shown to directly correlate with QoE [27, 28]. Thus it seems that waiting times related to the progress of page views are sufficient for predicting Web QoE.

However, several web studies confirm that web browsing is a rapidly interactive activity (cf. [53, 59]). Even new pages with plentiful information and many links tend to be regularly viewed only for a brief period - another reason to offer concise pages that load fast [42]. Thus, users do not perceive web browsing as sequence of single isolated page retrieval events but rather as an immersive *flow* experience (cf. [53]). In general, the flow state is characterized by positive emotions (enjoyment) and focused attention [9] and as a result, heightened human performance and engagement [58]. The

[3] The acronym WIMP denotes "windows, icons, menus, pointer", a style of interaction using these elements of the user interface.

notion of flow implies that the quality of the web browsing experience is determined by the timings of multiple page-view events that occur over a certain time frame during which the user interacts with a website and forms a quality judgment. This has a dual influence on the relationship between waiting times and QoE: on the one hand, flow experiences cause users to 'lose their sense of time', resulting in distorted time perception [9]. On the other hand, a sudden instance of overly long waiting time(s) abruptly ends the pleasant flow state and thus tends to be perceived particularly negatively [53, 60].

In addition, since during rendering page elements are typically displayed progressively before the page has been fully loaded, the users information processing activity tends to overlap with the page loading phase. In addition, the screen real-estate of the browser windows tends to be limited, with pages appearing to be complete before even having been fully loaded. As a consequence, the users perception of waiting time and latencies becomes blurred by the rendering process itself (which in turn is strongly influenced by page design and programming) [34, 53].

All of the above factors make the relationship between waiting times and QoE more complex than e.g. a file download, as the experimental results in the next subsections will demonstrate.

3.2. Experimental Results

On this part of the tutorial we will also discusses experimental results in the field of Web QoE and their consequences on questions of methodology and time perception. User-perceived performance cannot be simply derived from a direct mapping of page-load or session times to QoE. This is shown by the following three findings from a series of web-browsing QoE studies conducted in our labs at FTW: firstly, web-browsing is an immersive flow experience during which the user encounters a time series of waiting times (here also called page-load times or PLTs), beyond a single request-response transaction. Secondly, even if conditions in terms of QoS levels are held constant, PLTs fluctuate substantially during the course of browsing a web site. Thirdly, the subjective PLT as perceived by the end user and the technical PLT (typically measured on network or application level) tend to deviate from each other considerably.

3.2.1. Subjective Testing Methodologies for Web Browsing QoE

In contrast to audio and video quality assessment methodologies, where several accepted and even standardized testing methodologies exist, there is far less guidance for proper testing methodologies for web browsing QoE. One main difference towards audio and video assessment methods is the difference in user behavior as the user of a web page is not issuing a single request which is responded by one media experience, but rather a series of such request and responses as described in 3.1 is typical for web page usage. Figure 3a depicts the two request - response patterns involved in web browsing where T1+T2 or T3+T4 respectively, characterize the waiting time for one page view. As discussed in 3.1, a web session consists of several of such waiting times which are typically of different length (cf. Figure 3b).

A testing methodology for web browsing QoE must therefore ensure that such request - response patterns are issued throughout an evaluation. In order to achieve that two different approaches can be distinguished: 1) a certain number of requests or 2) a certain time for one web session. Approach 1) as used in [15, 22, 28] demands two requests and following responses and page views as depicted in Figure 3b (therefore addressing just a subset of page views of a whole web session as indicated by the zoom beam in Figure 3). After completing the user is then prompted for his quality rating on an ACR scale. The independent variable here are the T1+T2 and T3+T4 times. Contrary, approach 2) which was utilized in [48–50] uses pre defined session times. For each session the user is asked to execute a certain task on the given webpage while network parameters (e.g. downlink bandwidth, round trip time) are varied as independent variable. After the session time is elapsed the quality rating is gathered. Whereas approach 1) considers the overall session time as independent variable against which the MOS are plotted, approach 2) uses network level parameters as independent variable which then influences the waiting times for each request - response pair. While the latter approach guarantees a more realistic web browsing experience for the user resulting in a series of waiting times (cf. Figure 3b) the user is exposed to, the former approach allows to exactly control waiting times. Depending on the aim of the web browsing study to be conducted one has to decide for one has to weigh advantages and disadvantages os these two approaches.

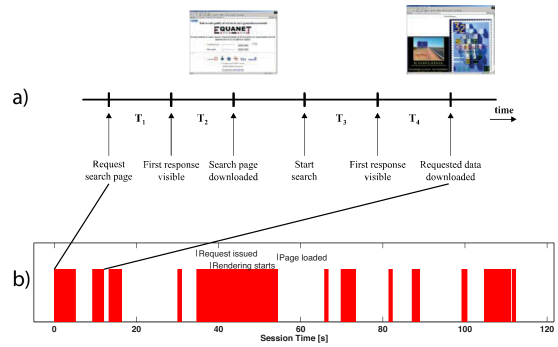

Fig. 3. a) Waiting times related to request-response patterns in web browsing [28] and b) Web session as series of page views with different waiting times.

3.2.2. Independent Variable: Page Load Time vs. Bandwidth

Next, we want to present results from two subjective user studies differing regarding the independent variable varied. In the first study the page load time has been varied whereas in the second study the downlink bandwidth was varied. The results of the two experiments are illustrated in the following way. The mean opinion score (MOS), i.e. the average over the subjective ratings for the same test condition, is plotted depending on the preset waiting time t with some markers. Additionally, as [12] assume that the relationship between waiting time and corresponding QoE is logarithmic, a logarithmic curve fitting $QoE(t)$ according to [12] is plotted as solid or dashed line.

Figure 4 shows the result for manipulated page load times (PLT task). The subjects were asked to browse through a picture album or to perform google searches. In both cases the request for the next picture and the search result were delayed for a certain time, respectively. The user study for the 'picture load' task was repeated twice. In addition, a 'photo' task has been conducted which differs from the 'picture load' task in the technical realization of the instrumented waiting time. For the 'picture load' (and the 'search') task, the HTTP requests were delayed, while for the 'photo' task the HTTP response instead of the HTTP request was delayed. However, this does not lead to observable differences from the end user's point of view. It can be seen that the assumed logarithmic relationship holds true except for the lowest load time $t = 0.18\,\mathrm{s}$ for the

’Photo task’ in Figure 4. This exception is in line with psychological time perception literature stating that duration estimation of waiting times below 0.5 s have to be treated different from longer waiting times [20]. This means that QoE reaches saturation for small waiting times and that the logarithmic relationship only applies above the saturation point, i.e. for noticeable waiting times.

The differences in the y-intercept for the different task can be ascribed to the difference in the tolerance thresholds for the different tasks.

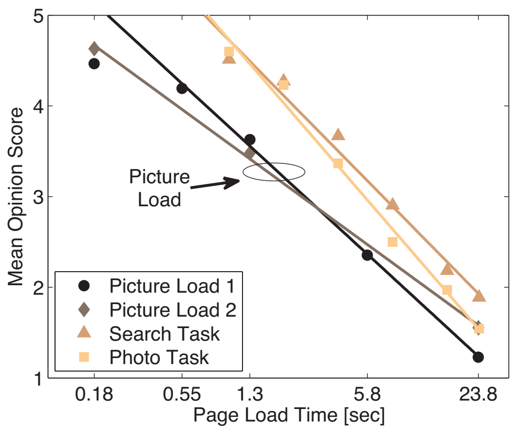

Fig. 4. User satisfaction for various constant page load times (PLT task) [12].

In the second study the users were asked to browse five different webpages while we manipulated the downlink bandwidth and gathered respective ratings for each bandwidth setting (details can be found in [50]). We assumed that these bandwidths could be recalculated into waiting times if the number of objects and their size are known as recommended by [28]. To be able to do that a posteriori we gathered these properties through passive traffic monitoring which we were running in parallel throughout the test.

Figure 5 shows the measured MOS and the corresponding logarithmic fitting in dependence of the downlink bandwidth. However, it can be seen that the logarithmic fitting does not match the MOS values very well. The major reasons for this mismatch are discussed below.

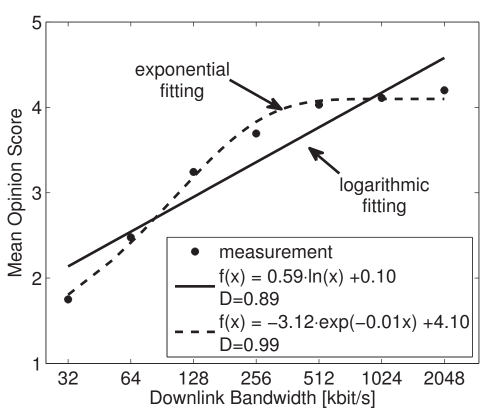

Fig. 5. Web browsing with downlink bandwidth limitation instead of instrumented constant page load times [12].

3.2.3. *Practical Issues with Web Browsing and Waiting Times*

1. Stimuli vs. Impairment. First of all, the logarithmic relationship relates waiting times to QoE. Similar to the Weber-Fechner law, a stimulus, i.e. waiting time, is related to user perception. However, bandwidth is not a stimulus in a strict psychological sense. Hence, the logarithmic relationship can only be applied if there is a linear relationship between bandwidth and time which is obviously not the case. In contrast, the IQX hypothesis introduced in [24] proposes an exponential interdependency between QoE and QoS parameters like bandwidth. Figure 5 shows in addition the corresponding exponential curve fitting which obviously seems to be quite appropriate to describe web QoE with respect to bandwidth.

2. Time vs. Bandwidth. The example of using bandwidth instead of waiting times for pages of a known size as shown in Figure 5 has already shown that the relation between bandwidth and QoE is different from the more simple scenarios where editing time was directly manipulated. One of the main causes for this difference is the fact that the relation between objectively measurable page load time and bandwidth is not linear due to the complexity and interactions of the HTTP and TCP protocol with the network performance (e.g. impact of high bandwidth-delay product on TCP performance; impact of TCP’s slow start, congestion and flow control on loading times of small pages; HTTP pipelining. cf. [5]). This leads to complex, non-linear models of *network-level page load times* for entire web pages. Furthermore, in addition to the network page load time, the local machine rendering and displaying the web page requires a certain amount of time. Hence, the *application-level page load time* differs from the network PLT and may vary dramatically for different types of web pages, e.d. due to the actual implementation, the used plugins, etc.

3. Perceived vs. Application PLT. As we have already seen, there are several factors yielding to non-linear relationships between bandwidth and (network and application) page load time. But even if we could achieve a mapping function outputting the exact objective (network and / or application) PLT this does not yet mean that this matches the subjective PLT as the example of perceived and objective time in Figure 2 has already shown. In addition, in web browsing a page might appear to the end-user to be already loaded although page content is still being retrieved, due to the progressive rendering of the browser, asynchronous content loading (AJAX) and the fact that pages are often larger than the browser window itself. To assess the resulting differences between subjectively perceived PLT and application-level PLT, we additionally asked participants in dedicated tasks to mark the point in time when they considered a page to be loaded, i.e. the subjectively perceived PLT. Figure 6 shows the ratio of the application-level PLT and the subjectively perceived PLT for different page types (and three different pages within each type, e.g. front page, search results and article detail page for Amazon). It can be seen that there are large differences between technical and perceived completion time, with ratios ranging from 1.3 up to 3 (where 1 would be the exact match between subjectively perceived and application level PLT).

Summarizing, all these different aspects lead to practical issues and challenges to measure or estimate the waiting time as perceived by the end user.

3.2.4. *Waiting Times for other Web-based Services*

Also other web-based services such as file downloads, e-mail retrieval etc. are also characterized by waiting times and are shown within this section. Figure 7 depicts the results of file downloads from [12] in which 2.5 MB and a 10 MB files were downloaded by

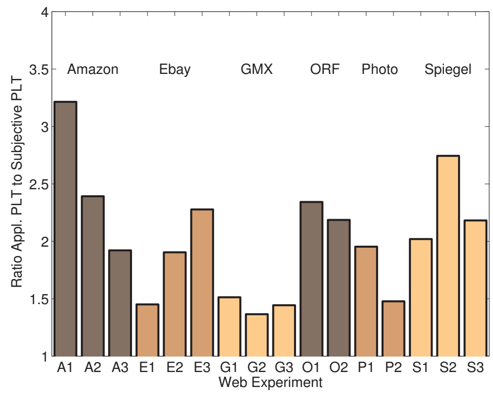

Fig. 6. Perceived subjective vs. application-level PLT for different pages [12].

the users. The measurement studies were conducted in 2009 first and repeated in 2011. It can be seen that the file size influences the evaluation of the waiting time on the y-intercept. The same waiting time results in significantly different MOS scores depending on the file size. For example, a waiting time of 38 s for the 2.5 MB files yield a MOS of 2.75 whereas the MOS of the 10 MB files was 3.58. This can be explained by the fact, that the expectation dimension of QoE (cf. [11]) interferes here. If people do know that the file size is large, they have different expectations regarding the respective download time to expect. As this expected time is longer in case of the 10MB files compared to the 2.5MB files, the ratings for the 10MB files are better. A further discussion on expectations and their influence on waiting time evaluation can be found in [3].

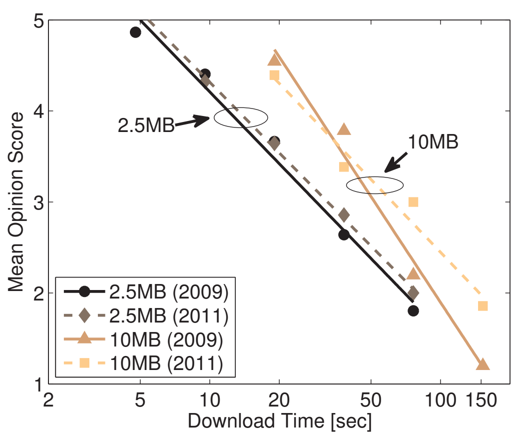

Fig. 7. Download of files of various sizes was investigated in two subjective user studies conducted in 2009 and in 2011, respectively (DL task) [12].

Figure 8 shows results from another study where waiting times were manipulated by [44]. In order to compare their results to the results we have obtained, we have also plotted logarithmic fittings. It can be seen that also these results can be closely approximated by the shown logarithmic fitting, hence coinciding with the results from our studies.

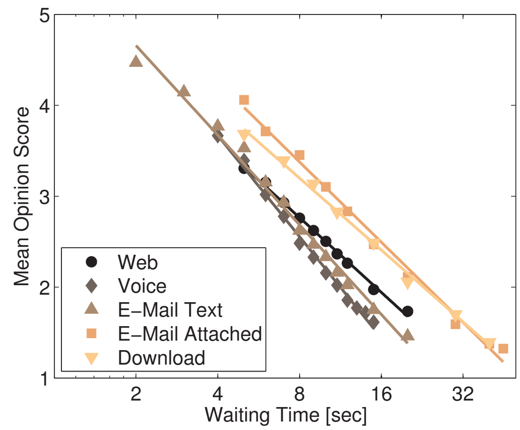

Fig. 8. Results from [44] supporting the WQL hypothesis, i.e. logarithmic relationship between MOS and waiting times, for several services.

4. WAITING TIMES IN VIDEO STREAMING

In the final part of the tutorial, we discuss relevant applications beyond web browsing where waiting times determine QoE amongst other factors. As major application, we consider Internet video streaming. While Section 4.1 discusses service interruptions causing the user to wait *during service consumption*, Section 4.2 considers the impact of initial delays, i.e. waiting times *before service consumption*.

For video streaming applications, service interruptions followed by waiting times are caused by rebuffering of the video due to 'bad' content delivery by the network or service provider. For example, if the video bit rate is larger then the available network (or server) data rate, the video buffer is emptied over time and then the video freezes until the video buffer is filled again with some video frames. Depending on the actual implementation of the video streaming application at the client side, the video frames which should be played out during the freezing period are either skipped or the video playout continues without skipping any video frames. The impact of freezing and skipping is discussed in Section 4.1.1.

In fact, the shift from unreliable media streaming to reliable HTTP (via TCP) streaming make waiting times one of the key QoE influence factors in the domain of web-based video streaming. There, the video rebuffering make the video freeze for some time and the rebuffering is visually indicated (e.g. by animated icons). To be more precise, we define *stalling* as freezing without skipping with a visual indication of the video rebuffering for the end user. In case of HTTP streaming, stalling is the major QoE influence factor. In particular, we will take a closer look at the impact of stalling and the resulting waiting times for the YouTube video streaming service in Section 4.1.2.

In general, user perceived quality suffers from initial delays when applications are launched. This will be disccussed exemplary for authentication in social network applications, 3G wireless connection setup times, as well as for video streaming applications to fill up the video buffer before the video playout, see Section 4.2.1. Finally, we show whether waiting times before or during service consumption are perceived worse, again on the example of YouTube QoE in Section 4.2.2.

4.1. Waiting During Service Consumption

4.1.1. Video Rebuffering and Freezing

Regarding service interruptions in video services most of the current work has focused on frame freezing caused by bursty packet losses. The authors in [39] and [46] have studied users' reactions to different disturbance patterns including frame freezing and skipping at the beginning, in the middle and at the end of the video. Their results correspond to each other in terms of the finding that the average ratings of disturbances in the middle of the video are perceived worse than those in the beginning and at the end. Additionally, [46] concludes that "viewers prefer a scenario in which a single but long freeze occurs to a scenario in which frequent short freezes occur." Also the current ITU-T recommendation on a objective multimedia quality model [29] considers frame freezing and frame skipping jointly.

Contrary, the studies reported in [61] and [26] do neglect impairments from frame skipping and concentrate solely on the impact of frame freezing itself. For HTTP video streaming, where frame skipping does not take place either, [23] and [40] have studied the impact of stalling events on user perceived video quality. Out of this overview, only the latter two studies have studied interruptions with rebuffering indication (stalling) as it takes place in HTTP streaming.

4.1.2. YouTube QoE and Stalling

There exist a variety of influence factors on QoE for YouTube video streaming. In general, four different categories of influence factors are distinguished, that are influence factors on context, user, system, and content level. The context level considers aspects like the environment where the user is consuming the service, the social and cultural background, or the purpose of using the service like time killing or information retrieval. The user level includes psychological factors like expectations of the user, memory and recency effects, or the usage history of the application. The technical influences factors are abstracted on the system level. They cover influences of the transmission network, the devices and screens, but also of the implementation of the application itself like video buffering strategies. For YouTube QoE, the content level addresses the video codec, format, resolution, but also the contents of the video, the type of video and its motion patterns.

Key Influence Factors. [23] focuses on quantifying the impact of stalling on YouTube QoE and varied 1) the number of stalling events as well as 2) the length of a single stalling event, resulting in 3) different total stalling times. In addition, they considered the influence of 4) the actual subjective test which were conducted in a crowdsourcing setting, 5) the test video id in order to take into account the type of video as well as the resolution, used codec settings, etc. Further, the users were asked to additionally rate 6) whether they liked the content (using a 5-point ACR scale). Additional data was collected concerning the background of the user by integrating demographic questions including 7) age, 8) gender, 9) family situation, 10) education, 11) profession, 12) home country, 13) and home continent. To get insights into the users expectations and habits in the context of YouTube, [23] additionally estimated 14) the user's access speed by measuring the time for downloading the video contents. Further, 15) the used browser was monitored by reading the user-agent field in the HTTP request header. Finally, the users were asked about their 16) YouTube usage and 17) Internet usage, i.e. how often the use YouTube or the Internet (several times per day, once a day, several times per week, once a week, several times per month, less often, never). These influence factors introduced are labeled accordingly in Figure 9.

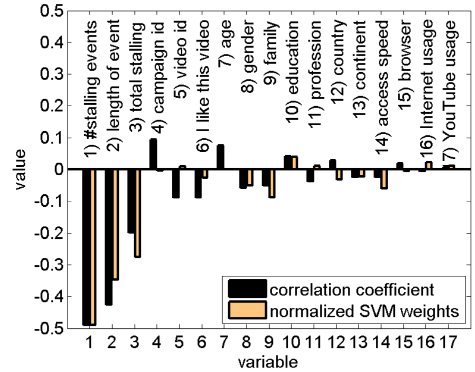

Fig. 9. Identification of key influence factors on YouTube QoE [23].

Finally, the key influence factors on YouTube QoE are identified in [23] by means of (a) correlation coefficients and (b) support vector machine (SVM) weights. The Spearman rank-order correlation coefficient between the subjective user rating and the above mentioned variables are computed. In addition, SVMs are utilized as machine learning approach to make a model for classification. Every variable gets a weight from the model indicating the importance of the variable. However, SVMs are acting on two-class problems only. For this, the categories 1 to 3 of the ACR scale to class "bad quality" and the categories 4 to 5 to class "good quality" are taken, respectively. Figure 9 shows the results from the key influence analysis. On the x-axis, the different influence factors ν_i are considered, while the y-axis depicts the correlation coefficient α_i as well as the SVM weights β_i which are normalized to the largest correlation coefficient for the sake of readability. We can clearly observe from both measures α_i and β_i, that the stalling parameters dominate and are the key influence factors. Surprisingly, the user ratings are statistically independent from the video parameters (like resolution, video motion, type of content like news or music clip, etc.), the usage pattern of the user, as well as its access speed to reflect the user's expectations.

However, it has to be noted that in these tests only typical YouTube videos were considered, however, more 'extreme' scenarios e.g. very small resolution vs. HD resolution are a subject of future work. Furthermore, the applied stalling pattern considers a bottleneck in the network or at the server side with a constant data rate. This leads to a periodic stalling pattern in which the duration of a single stall event has a fixed duration [25]. Hence, the impact of different traffic patterns on YouTube QoE is still to be investigated. Finally, the considered videos in the experiments [23] had a length of 30 s. However, [21] shows that the video duration impacts YouTube QoE and shows results for videos of 30 s and 60 s, respectively. Thus, a general relationship between the ratio of the stalling duration and the video duration onto YouTube QoE still is to be developed.

Mapping between YouTube MOS and Stalling. The identification of key influence factors has shown that YouTube QoE is mainly determined by stalling and both stalling parameters, i.e. frequency and length. For quantifying YouTube QoE, concrete mapping functions depending on these two stalling parameters were derived in [23]. To be more precise, YouTube videos of 30 s length were considered in the bottleneck scenario leading to period stalling events. Figure 10

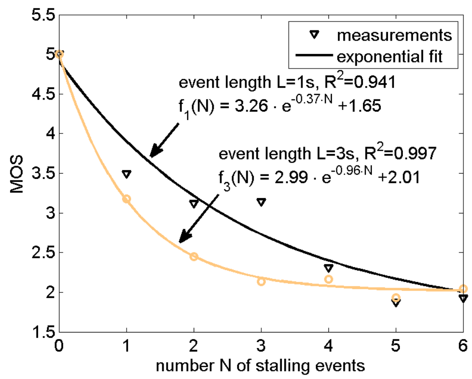

Fig. 10. Mapping functions of stalling parameters to MOS [23].

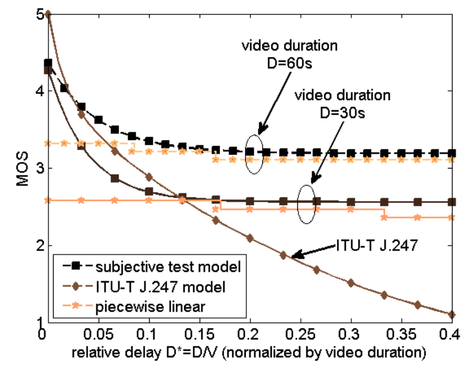

Fig. 11. Comparison of YouTube QoE model derived from subjective tests ('subjective test model') [21,23] with temporal model specified for freezing in ITU-T J.247 [29] and the piecewise linear model for HTTP streaming [40].

depicts the MOS values for one and three seconds stalling length for varying number of stalling events together with exponential fitting curves (as discussed in [15]). The goodness of fit is quantified by coefficient of determination R^2 and close to perfect match. The x-axis again denotes the number of stalling events, whereas the y-axis denotes the MOS rating. The results show hat users tend to be highly dissatisfied with two ore more stalling events per clip. However, for the case of a stalling length of one second, the user ratings are substantially better for same number of stallings. Nonetheless, users are likely to be dissatisfied in case of four or more stalling events, independent of stalling duration. Similar relationships and finding were reported in [21] as shown in Figure 11.

4.1.3. Comparison of Freezing and Stalling Models

[21] revisits freezing models found in literature and compares them with model functions describing the impact of stalling on YouTube QoE aIn particular, we consider the piecewise linear model for HTTP streaming [40] taking into account stalling events. Figure 11 shows the MOS depending on the stalling length D normalized by the video duration V, i.e. $D^* = D/V$. Although [40] converges to similar MOS values for long stalling events, the model fails in predicting accurately MOS for shorter stalling events below 4 s emerging in bandwidth limited scenarios for YouTube [25]. Furthermore, we apply the temporal model specified for freezing with skipping in ITU-T J.247 [29]. This model considers only relative delays. However, the comparison in Figure 11 shows that the freezing model is not applicable to stalling and completely neglects the influence of video duration.

4.2. Waiting Before Service Consumption

4.2.1. Initial Delays across Different Applications

The topic of waiting times before service consumption has been studied for several decades in the domain of market research where relations between initial delay, purchase decisions and discontent have been studied. In the domain of internet services the topic is rather recent and only little work has been published so far. Results from [12, 28] relate initial delays for web browsing and connection setup with QoE, whereas [37] has studied user perception of web logins and its related waiting times. For HTTP video streaming the authors in [40] have studied the impact of initial delays and integrated results from objective tests in their piecewise linear model. For IPTV services, which are affected by initial delays in the form of waiting times in channel zapping as well [35] have studied its impact on user perceived quality. What is missing from these results is a comparison of the initial delay impact on QoE across different services.

The scope of this section is on the impact of initial delays for different application scenarios [21] that comprise 1) YouTube video streaming, 2) authentication in social networks, 3) 3G Internet connection setup.

Figure 12 shows the mean opinion scores for the different application scenarios depending on the duration T_0 of the initial delay, together with errorbars representing the 95 % confidence interval over the M user ratings for the corresponding initial delay of the considered service. In addition, the MOS values of the subjective studies are fitted with a logarithmic function according to the WQL hypothesis [12]. This hypothesis is based on the fundamental Weber-Fechner law from psychophysics and applied to waiting times. It assumes that the relationship between 'W'aiting time and its 'Q'oE evaluation on a linear ACR scale is 'L'ogarithmic.

As a first observation, we see that the logarithmic function well fits the measurement results. In particular, we use a logarithmic function of the form $f(T_0) = -a \log(T_0 + b) + 5$ to cope with zero values ($T_0 = 0$ s) if no initial delay is present. The parameters a and b are determined by solving a non-linear minimization problem of the least-square errors between the MOS values at T_0 and the model function value $f(T_0)$. Reference [21] shows the model functions for the different applications which map the initial delay to MOS. In this paper we also show that for all measurement studies D is close to a perfect match. Thus, the WQL hypothesis cannot be rejected.

The second observation addresses the results for YouTube video streaming conducted in a laboratory test and a crowdsourcing test. Figure 12 shows the MOS values and the fitted logarithmic functions for the results from (a) the laboratory test (solid line) and (b) the crowdsourcing test (dashed line), when the users are watching a video of duration $V = 30$ s. The initial delay is varied from 0 s to 32 s.It can be seen that the differences between the MOS values from the lab test and the crowdsourcing test are not statistically significant. In particular, the MOS values for both experiments lie within the bounds of the confidence intervals. For readability reasons, we have also omitted the confidence intervals for the crowdsourcing test, since they anyway overlap with corresponding confidence intervals of the lab test.

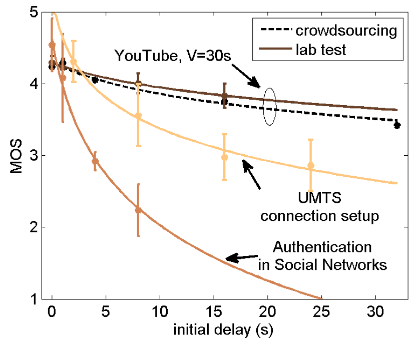

Fig. 12. Influence of initial delay on MOS across services [21].

Thirdly, we observe that the curves for the different services strongly diverge. This means that initial delays are perceived differently for different services. For example, an initial delay of $T_0 = 8\,\mathrm{s}$ leads to the following MOS values: (A) 4.00 for YouTube (lab and crowdsourcing). (B) 3.30 for 3G Internet connection setup. (C) 2.51 for authentication in social networks. These considerable differences across services for the same stimuli (i.e. initial waiting times) may be caused by the different application contexts and resulting user expectations. In particular, users learn from everyday interaction with an application how much waiting time is expected e.g. when logging in to a social network. Furthermore, the duration of the task itself may also influence the experience.

4.2.2. *YouTube QoE and Initial Delays*

[21] compares the influence of initial delays and interruptions for a certain time during watching on the user perceived quality. For this, we consider YouTube video streaming as application, since it easily allows to design and implement appropriate user studies for comparing the different influence factors, i.e. initial delay vs. stalling. It has to be noted that the user perceived quality of YouTube video streaming is compared in the presence of the same amount of waiting time. However, the waiting time materializes either as initial delay before service consumption or as stalling with an interruption of video watching. The results clearly show that service interruptions have to be avoided in any case, even at costs of increased initial delays for filling up the video buffers.

In particular, we analyze the subjective user ratings for the initial delay tests for YouTube videos of duration 30 s and 60 s. Regarding stalling, studies for 30 s and for 60 s video clips were executed in [21, 23]. The injected waiting times, either in terms of initial delay or in terms of one stalling event, range from 0 s until 32 s. Figure 13 shows the MOS and the corresponding 95 % confidence intervals depending on the introduced delay. In addition, the measurement results were fitted with appropriate functions. The results yield a set of interesting insights how temporal stimuli influence QoE.

Firstly, there is no statistical difference for video clips of 30 s and 60 s regarding the MOS in dependence of initial delays. This result seems counterintuitive, given the plausible presence of the recency effect. This effect means that e.g. if a drop to “bad quality” happens close to the end of service consumption, the overall MOS is stronger influenced than if the quality drop had occured earlier [56]. Thus for longer video durations, the inital “bad quality” event happened longer time ago which should lead to more positive ratings. However, recency effects cannot be expected in this case, since initial waiting times are considered here which are not clearly perceivable impairments such as stallings that visibly interrupt the service consumption and better match the concept of a ”bad quality” event.

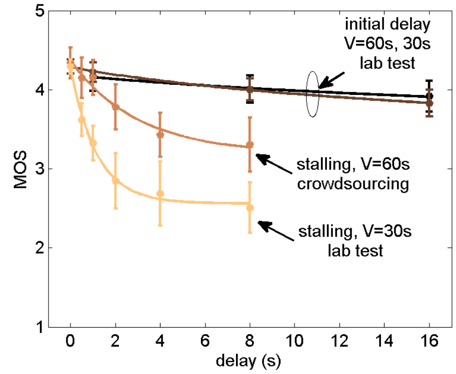

Fig. 13. One stalling vs. initial delay for YouTube QoE for videos of duration $V = 30\,\mathrm{s}$ and $V = 60\,\mathrm{s}$, respectively [21].

Secondly, for stalling the video duration matters. In contrast to initial delays, stalling invokes a service interruption by definition. This leads to clearly noticeable disturbance, i.e. a “bad quality” event, to which the recency effect applies. As a result, the MOS for the same stalling duration shows significant differences for 60 s and 30 s YouTube video clips which is e.g. 3.30 and 2.51 for a stalling event of length 8 s respectively.

Thirdly, the WQL hypothesis that suggests logarithmic dependencies between waiting times and QoE has to be rejected for the case of stalling. Instead, an exponential relationship leads to very good matchings[4] as postulated by the IQX hypothesis [15] which relates QoE and QoS impairments.

Finally, the results in Figure 13 clearly show again that service interruptions have to be avoided in any case from a user-centric point of view. Even very short stalling events of a few seconds already decrease user perceived quality significantly.

5. CONCLUSIONS

In this paper we have outlined structure and content of our tutorial on waiting times in quality of experience for web based services. Our examples show, that the study of waiting times in the context of interactive applications is a timely and relevant topic that is addressed best in an interdisciplinary fashion. Like QoE, time perception is highly subjective and context-dependent, but also adheres to certain fundamental principles. In this respect, the logarithmic relationships between waiting times and QoE demonstrate the applicability of well-known principles such as the law of Weber-Fechner. Furthermore, the interplay between immersion, (the disruption of) flow and QoE was shown to be relevant but complex – a property shared by many kinds of interactive multimedia applications. Consequently, we want to encourage researchers to further investigate these aspects and address them by adapting existing methods to the temporal characteristics of QoE.

[4]Coefficient of determination is 0.973 and 0.994 for exponential fittings instead of 0.945 and 0.817 for logarithmic fittings (for 60 s and 30 s videos).

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