Establishing Waiting Time Thresholds in Interactive Web Mapping Applications for Network QoE Management

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Abstract*—Customer expectations will continue to drive communication service developers to optimise their use of network resources based on user satisfaction. Thus, network platforms need to be remodelled from Quality of Service (QoS) centric to Quality of Experience (QoE) aware platforms. The perceived QoE for interactive web applications such as Google maps or Openstreetmaps is dominated by waiting time, i.e. the perceived time to render the page and map. Studies have explored waiting time estimation for Web QoE applications (e.g. email, downloads, web pages). Perceived waiting time for web mapping applications have been less comprehensively explored. The relationship between perceived waiting time and network QoS is a key QoE management factor to enable QoE aware networks. In this paper, we review the principle of network QoE management and the perception of waiting times. We present experimental design and methodology that facilitate the identification of waiting time thresholds for web applications, using web maps as a use case. We outline our results along with a statistical analysis and discussion interpreting the results and their applications. Finally, we discuss follow-up experiments and how they could be developed and applied in the network QoE management.

***Index Terms*—Web QoE, QoE Management, Waiting Time**

I. Introduction

In computer networks, Quality of Service (QoS) has been the primary basis for performance and policy optimisation for the applications and services [1]. The network performs optimisation based on common QoS metrics such as latency, jitter, drops and throughput. QoS metrics measure the network perspective in an objective manner but do not capture a user's perception of the quality. Quality of Experience (QoE) considers user experience factors beyond the system, i.e. context, user, content and system (Fig. 1). It can provide further insights into the end user's quality perception [1] and user satisfaction. Mean opinion score (MOS) is common QoE metric which measures the level of user satisfaction. The International Telecommunication Union (ITU) defines opinion score as the value on a predefined scale (e.g. Absolute Category Rating (ACR) scale) that a subject assigns to his opinion of the performance of a system. MOS is the average of opinion scores across subjects [2].

Network QoE management is an emerging field where networks are QoE aware and network dynamics are optimised [1, 3, 4]. The link between network QoS and QoE is an active area of research [5, 6, 7], particularly for multimedia applications using video streaming or voice over IP. More recently network based QoE management has sought to apply the same principles of QoE for the other applications including web applications (Web QoE) [6, 7, 8].

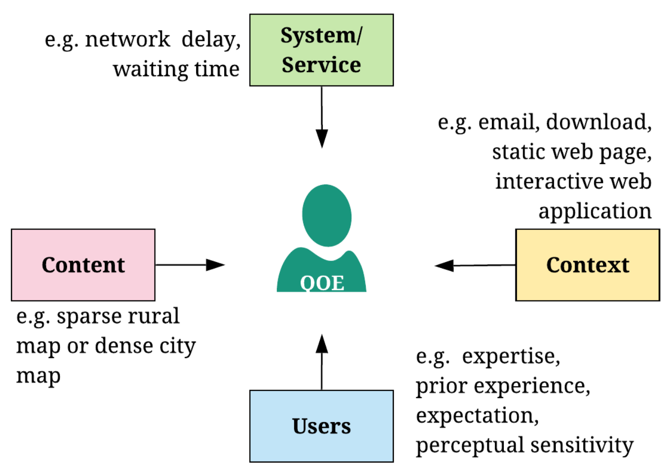

Fig. 1: Illustration of quality of experience influence factors based on a web mapping application.

The term Web QoE refers to the quality of experience of interactive applications that are based on the HTTP or HTTPS protocols and are accessed using a web browser [9]. Web applications follow a request-response paradigm in which the user makes a request, the server processes the request, and issues a response. The network transports the data between the web server and the user's browser. The HTTP request and response processes result in a series of waiting times or Page Loading Times (PLTs).

Results from earlier Web QoE studies demonstrate that waiting time is a predominant impairment for web QoE, which exhibits a logarithmic relationship with user's satisfaction [6, 10]. Waiting time influences a user's patience, the longer that a user waits beyond their expectations, the less satisfied the user becomes. Waiting time correlates with user perception and is a major metric in the network QoE management for web applications. However, it is challenging to determine a proper waiting time for interactive web applications (e.g. Google Map and OpenStreetMaps) [6].

Waiting time is influenced by a variety of factors such as the size of content data, the application and the network. A user is not necessarily aware of, or interested in, the cause of waiting times. They expect the web application response to have a preconceived speed based on expectations that can be set by their prior experiences.

Perception of time has long been known to be relative. Perceived waiting time and actual waiting time are not as tightly coupled as might be imagined for interactive web applications particularly due the the influence of user expectations. A waiting time increase of one second over an expectation of 50*ms* has a significant impact on QoE but the same one second added to a longer expected waiting time of 20 *seconds* could have a negligible effect on QoE [10]].

Therefore, with regard to Fig. 1, by fixing the context to an interactive web mapping application and the content to a sample map we formulate the hypothesis that the perceived waiting time is a function of user's expectation and the actual waiting time.

The dominant methods in studies analysing time perception are just noticeable difference (JND) and absolute threshold identification. JND is the ratio of perceived time to actual time, specifically the minimum difference between two stimuli that a human can perceive 50 percent of the time. While JND determines perceptible differences in stimulation levels, absolute threshold identifies the smallest detectable level of stimulation [11].

In this study, we used the paired comparison paradigm common to JND and absolute threshold and used in time perception studies to establish the perceptible change threshold for five waiting times that correspond to perceived quality levels for web pages from [6]. Thus, the change threshold can be used to inform optimisation strategies for network QoE management.

There are a number of assumptions which are present necessary to support the purposed study. These assumptions include:

- Map QoE will follow a pattern similar to web page QoE (Fig. 2).
- The five *base* quality levels will illustrate the trends of waiting time for mapping application QoE.

These lead to choosing 5 base waiting times that correspond to the web page waiting time for MOS scores at level 1-5.

II. Human Time Perception and Web QoE

Human time perception was one of the earliest topics to be explored in psychophysics and has been extensively studied by researchers. Psychophysics is the scientific approach of investigating relationship between perception and physical stimuli. The perception of time in human is a major factor when a person has to decide and judge the outcomes associated with their actions [11, 12].

The human brain does not act as a linear measuring device and estimates derived from a perception of duration cannot be assumed to be the same as the actual duration. There is no dominant mapping between external magnitudes and internal sensations that can be explained by a simple mathematical function.

In the area of Web QoE, numerous studies have attempted to explore the roles of human time perception and physical time from the QoE perspectives.

In [13], the authors present a platform for crowdsourcing Web QoE measurements. The platform allows the researchers to investigate how to measure web "page load time" (PLT) in a way that captures human perception. Varvello et al. demonstrate that objective measurement of PLT metrics fail to represent the actual human perception of PLT.

Reichl et al. [10] and Egger et al. [6] demonstrated logarithmic relationships between QoE and waiting/response times and explained it on the basis of Weber-Fechner law (Fig. 2). Egger et al. proposed a hypothesis which asserts that "the relationship between Waiting time and its QoE evaluation on a Linear Absolute Categorical Rating (ACR) scale is Logarithmic" (WQL).

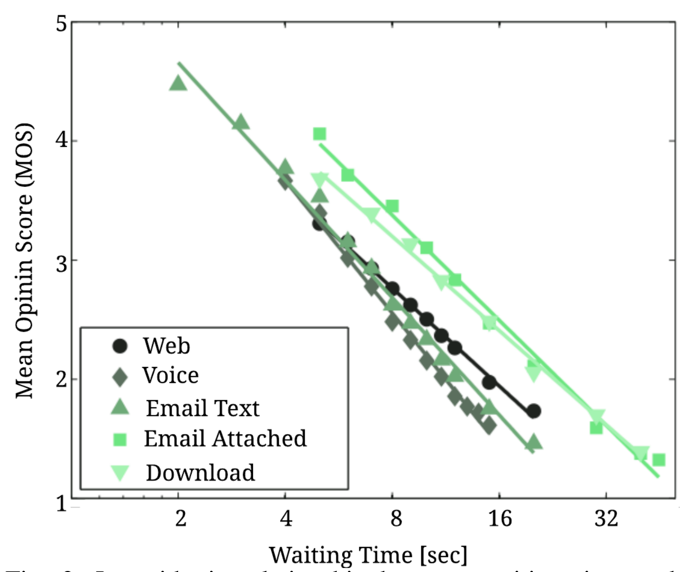

Fig. 2: Logarithmic relationship between waiting time and Mean Opinion Score (MOS) [6].

In this paper we present a methodology and experimental test platform to investigate the perceptual thresholds of waiting time for interactive web applications. Based on the comparison of a base waiting time for *map A*, is *map B* perceived as slower or faster and thus have the potential to impact QoE?

Identification of waiting time thresholds for interactive web applications will enable network QoE management that is aware of the impact of small waiting time changes compared to the QoS the network is providing, offering the opportunity for realtime adaptation to improve QoE. The proposed experiment

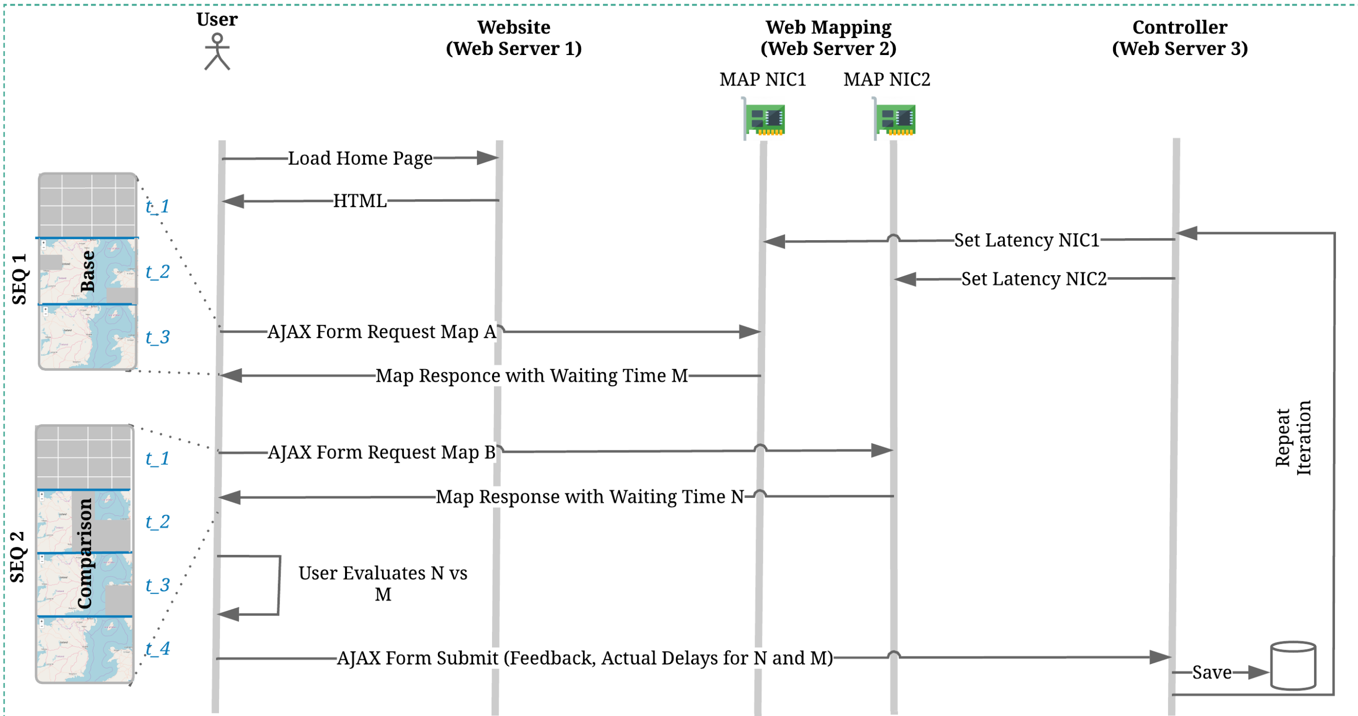

Fig. 3: Subjective experiment process sequence. It can be seen that the waiting time associated with web mapping is applied by utilising the two network interfaces and manipulating the network delay. The user feedback, whether the speed of loading Map B in compare to Map A was: *Definitely Slower, Slower, Not Sure, Faster* or *Definitely Faster*.

will explore the waiting time thresholds and identify the boundaries at which time they become perceptibly different. The experiment will be carried out for a range of times corresponding to user expectations, i.e. how are changes in waiting time experienced for different MOS levels [2].

III. Subjective Test

The primary objective of this experiment is to investigate perceived waiting time thresholds by exploring the relationship between objectively measured waiting time and the perceived waiting time for a given perceived quality level (MOS) in Web QoE. The subjective test discussed in this paper is tailored for web mapping applications. Web mapping applications use raster image tiles to present a map view that can be zoomed or panned. Each image tile is a PNG file. The PNG file format allows a browser to first render the image with a lower quality (blurred), followed by one or more iterations that refine it until the final and full-resolution image is shown. This is known as interlacing method. Interlacing is aesthetically pleasing when compared to a sudden discontinuity step change from a solid void to an image at the end of the image buffering time.

In this paper, we define waiting time for the web mapping application as the amount of time taken for a tiled map to load all required tiles fulfilling a single user action.

The proposed subjective experiment was reviewed and approved by University College Dublin Office of Research Ethics.

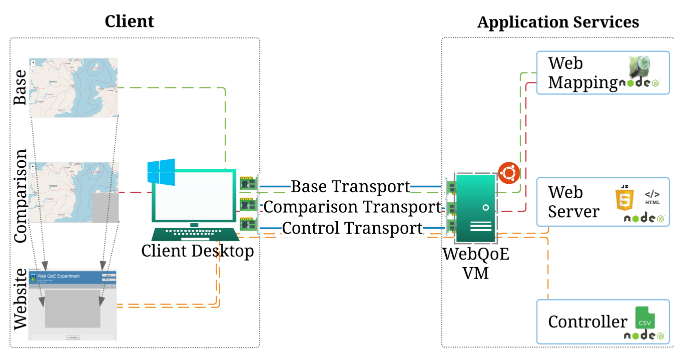

Fig. 4: Experimental platform for studying perceived waiting time. The platform simulated a real network environment and consisted of 2 node servers, a web server and three network transport NICs as described in section III-C.

A. Design and Methodology

The experiment is designed on the basis of ITU-T Rec. P.1501 [14] and uses conventional psychophysical approach for studying time perception [11, 12] for a web mapping application. Time perception is a prothetic dimension meaning that sensory analysis establishes the quantity rather than the quality of the stimulation [15]. Pair comparison is a known approach in conventional psychophysical studies in which, two time intervals are presented on each trial: a *base* with fixed value across trials, and a *comparison* with varying duration [11]. The observer indicates which interval was longer (or shorter), the responses are used to estimate the relationship between the human time perception for a given stimuli and the physical time [11]. Thus, the pair comparison method facilitates the establishment of time perception thresholds.

In this experiment (Fig. 3, we present two web maps in each iteration: a *base* case that has a fixed waiting time across a group of iterations (based on the quality level), and *comparison* cases, with varying waiting times. The presentation sequence between *base* and *comparison* cases are randomised to minimise bias. The map shown in the first sequence is labelled *Map A* and the second sequence is labelled *Map B*. The participants then compare the loading of *Map B* versus *Map A* and feedback whether Map B was perceived as: *Definitely Faster*, *Faster*, *Not Sure*, *Slower* or *Definitely Slower*

Participants are given training before the actual experiment to familiarise themselves with the platform as well as the sample range of waiting times in the test. The main objective of the training phase is to encourage the participants to use the full range of the feedback scale.

It is explained to the participants that if you have not perceived any difference between loading of *Map B* vs *Map A*, they should choose the *Not Sure* option. When they felt the difference but not very confident, they may select *Faster* or *Slower*. They should choose *Definitely Faster* or *Definitely Slower* when they were confident about their judgement. From this feedback, we expect to measure the participantss internal "perceptual scale" for the waiting time associated with the loading of the map for different quality levels.

B. Experimental Parameters and Scales

Ten volunteers (mean age = 28 years, range 23–35 years), took part in our preliminary experiments (The number of participants will be increased in our future studies). All participants had normal or corrected to normal vision. The duration of this experiment was 18 to 20 minutes per participant. Iterations are divided into five distinct quality groups (Shown in TABLE I).

MOS	Base Value (ms)	Comparison Values (ms)
5	33	85 90 145 195 244 283 289 324 344 463
4	2109	2181 2482 2623 2941 3131 3247 3397 3627 4096 4180
3	3569	4707 5036 5599 6057 6404 6321 7076 8300 10142 10256
2	9113	10640 11072 11912 13056 13446 14350 14835 15324 16085 17270
1	16174	17454 17667 18709 19231 21765 22034 23479 25249 26057 30110

TABLE I: The base time values are chosen with reference to the web applications from [6] reproduced in Fig. 2. The comparison numbers were chosen to be a roughly linear increment for 10 samples across the desired range.

Based on our initial assumptions, each quality group corresponds to a base case waiting time for a MOS quality level. At each group, there are 10 unique values for *comparison* and a single *base* value. Each pair of *comparison* and *base* is presented twice but in different sequences. This allows us to understand whether the order of presenting *base* and *comparison* impacts user's perception or not. The *base* waiting time value for each quality level is assumed to be similar as web page loading time (Fig. 2) and obtained from the previous Web QoE study conducted by Egger et al. [6].

Two different methods can be used to apply variation in waiting times: instrumenting application or by applying network distortions. We use network distortion to increase the waiting time and keep the aesthetics factor intact. This allows us to investigate the perceived waiting time based on a realistic experience for the end user. In order to ensure that the experience associated with the waiting time for map loading was similar to the real-life web mapping experience (e.g. the same tile loading experience that a user would be familiar when navigating with Google maps), a simple browser only based experimental setup was insufficient. While we could instrument the web mapping application using a JavaScript function and load each tile after x amount of time, a sudden discontinuity step change image load would occur. Over a high speed and congestion free network connection, PNG interlacing mechanism is not perceptible. We performed an experiment observing that when a grey box turns into a high resolution map tile, it biases user's perception. Therefore, controlling waiting time through instrumenting the web mapping application excludes perception of PNG interlacing mechanism, thus, impacting contribution of the web site aesthetics on QoE [16].

By changing network delays we achieve the expected waiting time for the *base* and *comparison* map loads. Expected waiting time and actual waiting time are monitored for each test. Due to the system and resource constraint (e.g. operating system background processes, I/O buffers and memory), there is a slight variation for the targeted *base* and *comparison* values. Any collected records with *base* values that differ more than 10% from the expected value are discarded.

C. Technical Implementation

The platform (Fig. 4) is utilising virtual box hypervisor installed on Dell OPTIFLEX 5040 With Intel(R) Core(TM) i7-6700 CPU @ 3.40 GHz and 16.0 GB of RAM. It is composed of two components: WebQoE Virtual Machine (VM) and a Windows Desktop Machine as a client (The same host as the VM hypervisor).

The WebQoE VM is an Ubuntu 12.04 X86 64 bits with one CPU, 4.0 GB of RAM and three network interfaces: *Base*, *Comparison* and *Control* transport interfaces. A unique block of IP addresses is assigned to the each network interface. The reason behind having three different interfaces is that during the experiment, the network delay on the *base* and *comparison* transport interfaces gets manipulated, but the existence of *control* transport interface keeps the communication between the client's browser, the web server and the controller intact.

The WebQoE VM hosts three web servers:

1) Web Mapping: Developed using NodeJS. The service is listening over both *base* and *comparison* network interfaces.

Web mapping service provides a map of the world that contains a tiled map. Tiled maps are downloaded as several tiles. Each tile is an image but different in size and usually square. Tile images are placed side-by-side to construct the maps. Web mapping service receives HTML request that includes the latitude, longitude and zoom level of the location then; it builds the specific tiled map from its local database and transfers it back to the client's browser.

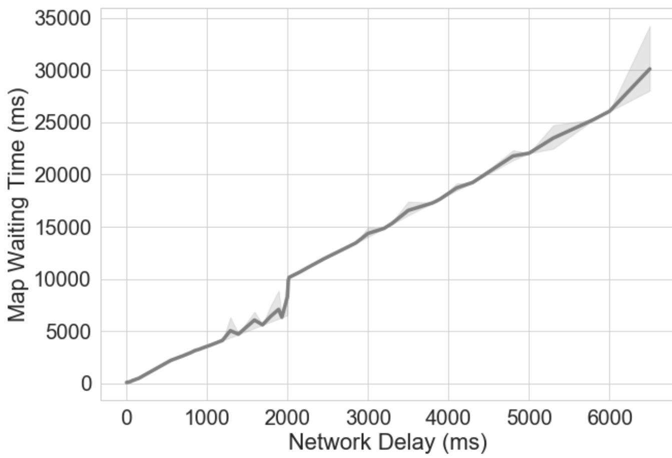

Fig. 5: Relationship between network delay and waiting time associated with map loading.

2) Controller: The controller is a NodeJS-based application, which listens over the *control* transport interface. In a previous study [17] we demonstrated a strong relationship between map loading time and the network delay. Therefore, we manipulate network delay to achieve the targeted waiting time associated with the loading of the maps. The corresponding values of network delays (Fig. 5) for the targeted waiting times are derived from an automated version of the same platform (the sudden increase on waiting time at 2000ms of network delay is due to the TCP re-transmission timeout (RTO)). For each iteration, the controller changes the network delay of both *base* and *comparison* transport interfaces to achieve the targeted waiting time for the *base* and *comparison* maps. The controller also receives users feedback and stores it in a CSV file.

3) Website: It is bounded to the *control* transport network interface. It hosts the HTML pages of the Web QoE experiment website. The main HTML page of this experiment is developed using Leaflet, AJAX and JavaScript. It has some essential features: 1)The *base* and *comparison* maps load using two distinct transport paths. 2)Once the user submits HTML request (e.g. Load Map A), HTML elements can load without refreshing the page. 3)A combined AJAX and JavaScript function captures the map loading time, user's feedback and passes the information to the controller using a *control* transport path. 4)Each iteration is done with two mouse clicks without moving the mouse cursor (time perception studies show that time judgements are influenced by a secondary tasks [18]).

IV. Results and Discussion

In this subjective experiment we collected 419 valid data points with approximately 41 data points for each participant. For these repeated-measures, that are not normally distributed, we have used a Generalised Linear Mixed Model (GLMM) in which the data are permitted to exhibit correlated and non-constant variability.

A. Validating the Methodology

As a pre-requisite and validating the described methodology, we are investigating whether a relationship exist between the actual difference in map load times and the perceived load times as defined by the user's feedback (e.g. *Definitely Slower*, Slower, Not Sure, Faster or *Definitely Faster*). This helps us to validate whether the feedback choices are properly reflecting the users perception or not.

The hypothesis is: there is a relationship between the actual load time difference of *map A* and *map B* and the perceived difference as indicated by the users feedback scores.

To validate this while accounting for the random effects of subject, and the categorical nature of the feedback scores, we tested to see if there was a significant difference between the feedback scores in terms of the associated load time difference between Map A and Map B: $F(9, 419) = .49; p > .05; \eta_p^2 = .01$. Following the F notation from the result, the first number in parentheses refers to the numerator degrees of freedom and the second number corresponds to the denominator (error) degrees of freedom. There are p-values for each effect and the partial η^2 refers to the effect size of the test. The result show that participant specific random effects were not significant (e.g. The fact that different participants did different amounts of trials didn't bias the results) and also feedback categories significantly differed in terms of the difference scores: $F(4, 419) = 33.917; p < .0001; \eta_p^2 = 0.25$.

Multiple pairwise comparisons demonstrated that these feedback categories differed in terms of their difference scores in the expected direction (e.g. getting slower or faster), where the feedback category *Definitely Slower* was significantly slower than all other feedback categories. The *Slower* feedback category was significantly faster than the *Definitely Slower* category and slower than all other categories. However, there was no significant difference between the *Faster* and the *Definitely Faster* categories in terms of the difference scores.

B. Analysis of accuracy of waiting time perception independent of quality level

The waiting times used in the experiment were guided by the relationship between waiting time and MOS for web applications in Fig. 2. We wish to verify for all data in general, whether the user perception of waiting time changes is consistent when the map loading time is getting slower versus faster.

The hypothesis is: For all waiting time lengths a user can better discriminate the difference in waiting time when the second map has a lower waiting time.

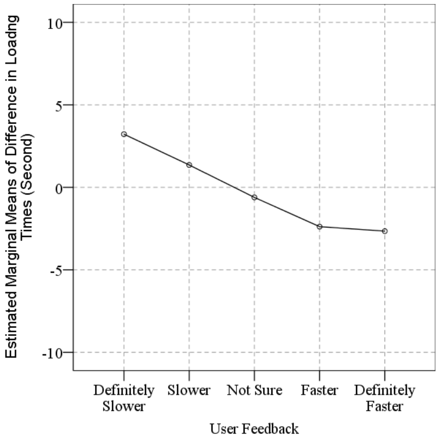

Fig. 6: Estimated Marginal Means of Difference in Loading Time of *Map A* versus *Map B* Independent of Quality Level.

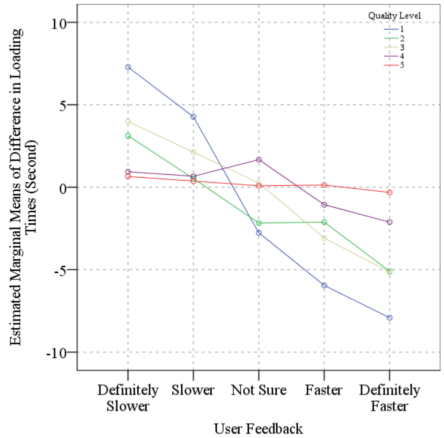

Fig. 7: Estimated Marginal Means of Difference in Loading Time of *Map A* versus *Map B* Dependent of Quality Level.

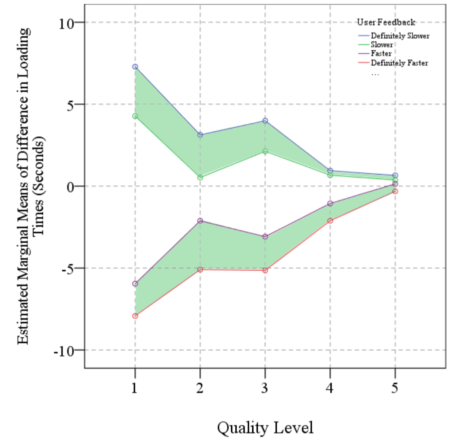

Fig. 8: Perceptible Change Thresholds and Estimated Marginal Means of Difference in Loading Time of *Map A* versus *Map B* Dependent of Quality Level.

In order to validate the above hypothesis, we have calculated estimated marginal means of difference in map loading times regardless of MOS levels and plotted versus the feedback score. The Estimated Marginal Means tells us the mean response for each factor (difference in loading time), adjusted for any other variables in the model (feedback).

As shown in Fig. 6, the slope of the line between *Faster* and *Definitely Faster* is not as steep as between *Slower* and *Definitely Slower*, suggesting that the test subjects were found it more difficult to distinguish the difference when the load time decreased. This demonstrates an asymmetry in waiting time perception and that users have a stronger ability to perceive differences when the loading time increases than when it decreases.

C. Analysis of accuracy of waiting time perception dependent of quality level

We wished to establish whether the user perception of waiting time changed when the map loading time is getting slower versus faster and whether this was consistent across MOS levels.

The hypothesis is: the relationship between the perceived difference in map loading time is dependent on the quality category of the load times.

This model repeats the previous test but it also includes the effect of the interaction between feedback and quality levels. The result shows that participant specific random effects were not significant: $F(9, 399) = 1.11; p > .05; \eta_p^2 = .024$ and also feedback categories were significantly associated with the difference scores: $F(4, 399) = 48.05; p < .0001; \eta_p^2 = 0.33$.

It should be noted that the effect of feedback significantly interacted with MOS levels meaning the relationship between feedback and the difference in the load time, is related to the quality level: $F(20, 399) = 7.139; p < .0001; \eta_p^2 = 0.2$.

In Fig. 7, the estimated marginal mean of difference in loading time is plotted per MOS level against the feedback categories. The slope of lines in Fig. 7 show that, the higher the MOS quality level, the more sensitive the user becomes to the changes in load time. Minimal changes in the load time are more likely to be perceptible by users. Interestingly, when the application quality is high (MOS level 4 or 5), the subjects showed better discrimination when the load time increased over when it decreased.

D. Towards QoE Management

Fig. 8 presents the estimated marginal means of difference in loading time of *Map A* versus *Map B* based on the quality level (MOS). By visualising the data broken down by user feedback category (excluding *Not Sure*) we can see the potential to establish threshold waiting time changes to maintain or elevate MOS for a given quality level. In Fig. 8, consider quality level of MOS 4, from Fig. 2 we can see that MOS 4 corresponds to a waiting time of approximately 2.5 seconds. From Fig. 8 it can be seen that the mean difference in loading time changes by approximately 900 ms as user experience changes from *Faster* to *Definitely Faster*. Additionally we see that the mean difference in loading time changes by approximately 300 ms as user experience changes from *Slower* to *Definitely Slower*. The time gaps between the user feedback categories have been shaded in the figure and change by the quality level. If, through further experiment, these can be accurately measured and validated they could potentially be used to inform the network orchestrator whether expending network resources to alter a user's waiting time by a given amount would have a *Definitely Faster* impact on their QoE. Conversely, resources could be saved if they do not shift the experience to be *Definitely Slower*.

V. Conclusion and Future Work

Interactive web applications such as online gaming, mapping applications, real-time equipment management manufacturing and health applications incur waiting times for their users. Waiting times associated with such applications are on different timescales, e.g. for a video to start; for the web form to become updated; for the game to react to one's input. Waiting time is a key metric for QoE/QoS correlation in the network QoE management for such applications. However, the perceived waiting time does not correspond directly with measured waiting time. For effective network QoE management where the network is aware of the influence small changes in delay can have on the Web QoE for an end user and can adapt the service accordingly, it is important to establish the thresholds associated with the waiting time and their relationship with QoE. The methodology and results presented in this paper facilitates the identification of waiting time thresholds for web mapping applications. We plan to use the proposed method and experimental framework to further experiment:

1) Using a slider option for the a continuous scale feedback to identify waiting time thresholds for the web mapping applications.
2) Explore the influence of content on QoE and waiting time using different map building density.
3) Repeat the map with an adapted test setup using a single map to rate QoE on ACR scale. This will allow the results of the experiment to be compared to other web apps experiments that using a MOS scale.

We anticipate that through providing waiting time thresholds and a perception model, networks could be developed where unnecessary optimisation is minimised and polices are developed to either noticeably impact the end users perception or to reduce the allocated resources for a particular application without impacting the end user's QoE.

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