Impact of Human and Content Factors on Quality of Experience of Online Video Streaming

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Abstract: Although expensive, but the most reliable measure of user perception is by direct human interaction by taking input from the user about a stimulus quality. In our previous studies, we have identified some subjects getting bored and losing focus by rating lots of video clips of small duration during subjective quality assessments. Moreover, the psychological effects, i.e. user delight, frequency of watching online videos (experience), mood, etc. must not influence the user Mean Opinion Score (MOS) for determining the quality of the shown stimuli. In this paper, we have investigated the impact of user delight, frequency of watching online video content (experience) and different mood levels on MOS for streamed video stimuli in various network conditions by subjective quality assessments. We have observed a slight tendency of better scores when the user likes the stimulus. However, our results show that if the subjective assessments are conducted by carefully following the guidelines, the users impartially rate the video stimuli solely based on the quality artifacts irrespective of their delight towards the shown content. Although, we have observed an effect of user mood on MOS ratings; for almost all the stimuli, but the results suggest the need of more detailed study; i.e. with a large and diverse set of subjects, to obtain significant statistical relevance.

1 INTRODUCTION

The video traffic accounts for 75% of global Internet traffic with per-capita share of 16 GB in 2017 and it's forecasted to reach a share of 82% with per-capita of 50GB by the year 2022. There would be more than 28 billion estimated networked devices and the share of traffic generated by wireless and mobile devices is forecasted to reach around 71% (Cisco, 2018). This shows a clear trend of watching online video content on the go, i.e. IPTV, video on demand, etc. The result is 11-year low subscription rate of television service in United States due to the low-cost and flexibility associated with online video streaming alternatives as per American Customer Satisfaction Index of 2018 (Johnston, K., 2018). According to the same report, the video streaming services have grown exponentially in the previous years and there is no indication that the trend is slowing down. Thus, there is a massive interest and stake associated with the user experience for both Internet service providers and video content creators. *The Quality of Experience* (QoE) is defined by ITU-T as *'The degree of delight or annoyance of the user of an application or service.'* (ITU-T Rec. P.10/G.100, 2017), with reference to the full definition that continues with *'It results from the fulfillment of his or her expectations with respect to the utility and / or enjoyment of the application or service in the light of the user's personality and current state'* (Qualinet, 2013).

The effects of neglecting QoE are evident from the latest report of comparing Internet service quality in UK, which suggests that 84% of the customers' complaints for fixed broadband were related to slow speeds and intermittent or total loss of service with only 12% complaining about billing, pricing or payment (Ofcom, 2019). Although expensive, the most reliable measure of user perception is by direct human interaction and subjective assessments are done by taking direct input from the user about a stimulus quality via conducting a survey. The *Mean Opinion Score* (MOS) is defined by ITU-T in (ITU-T Rec. P.910, 2008) and has become a de-facto standard due to its wide range of adoptability for speech quality and multimedia applications. The validity of these qualitative subjective tests is primarily dependent on obtaining the user response in a tightly controlled environment. There are many factors that may influence the user ratings and recommendations have been provided by ITU-R to control the monitoring con-

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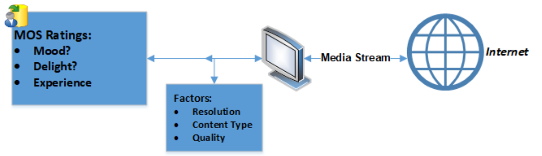


Figure 1: User information including watching frequency.

ditions (ITU-R Rec. BT.500-10, 2012). The term Influence Factor (IF) is defined as *'Any characteristic of a user, system, service, application, or context whose actual state or setting may have influence on the Quality of Experience for the user'* (Qualinet, 2013). This elaborates that these IFs have a tendency to affect the MOS. The QoE measurement was primarily centered on the system IFs; such as perceived video quality in different network conditions or video encoding protocols/algorithms irrespective of environment of the experiment; i.e. in emulated environment or user-centric situations in real life. One common objective in all these studies is to benchmark the QoE objective metrics with subjective quality assessments or/and QoS parameters. This is partly due to the challenges related to the operationalisation of the wide spectrum of potential influence factors, but it could also be associated with the shortcomings of current practices. It's important to mention that although the effectiveness of MOS is questioned by many studies regarding whether the difference between excellent and good is equivalent to distance between fair and poor, etc. but the critical observations and interpretations have not been unequivocally in this regard (Streijl et al., 2016; Pinson et al., 2012).

In this paper, we have extended our previous study (Minhas et al., 2019) to investigate the impact of user delight towards the shown content (ITU-T Rec. P.10/G.100, 2017; Qualinet, 2013), frequency of watching online video content (experience) and different mood levels on MOS for streamed video stimuli in different network conditions as shown in Figure 1.

As the MOS is a group-based perceived quality indicator of a stimulus, we expect the user ratings to be independent of these emotional effects (Minhas et al., 2019). Finally we have obtained MOS ratings from ITU-T recommended Perceptual Evaluation of Video Quality (PEVQ) software for multimedia quality measurements (ITU-T Rec. J.247, 2008). We have benchmarked PEVQ MOS with real MOS of all subjects and MOS values of different user groups' in terms of delight, experience or mood. The result of benchmarking is an interesting indicator to validate and justify the subjective assessments in comparison to a typical objective assessment.

The paper is structured as follows: In Section 2, we provide an overview of the related work. Section 3 gives a brief overview of the related technologies. The detailed experimental setup information with important parameters is shown in Section 4. The assessment results and corresponding interpretations are available in Section 5. Finally, the conclusions are outlined in Section 6.

2 RELATED WORK

There are many studies that highlighted the effect of human psychological states on her behavior and perception of a service. Moreover, many psychological studies have shown the impact of stimuli on evoking human emotions and influencing the user behavior.

(Schleicher and Antons, 2014) have summarized the effect of evoking emotions on the user behavior based on visual, audio and audiovisual stimuli. The stimuli used in those studies were categorized as pleasant, unpleasant and neutral based on the contents. They have observed that video clips of a film have a far-greater impact on evoking emotions as compared to pictures and brief sounds. Their study also suggests that the user may be asked to rate their emotions to obtain a mean opinion score similar to the perceived quality evaluation.

(Zhu et al., 2015) have observed the influence of human factors such as age, gender, watching frequency, cultural background, etc. in terms of social context (co-viewers). The quality ratings were collected in a controlled laboratory setting and via open-source software and benchmarked. They have observed that social context does play a role in user's enjoyment.

(Engelke et al., 2012) measured the rating time involved in assigning a score to stimulus during qualitative subjective assessment. The experiment was focused on obtaining MOS of images subjected to network impairments during transmission on a wireless network. The scope of the study was quite limited as only 15 subjects took part in the assessment and ratings times were recorded manually using a stop watch which may compromise the accuracy. The authors did notice correlation of rating time with the MOS score and influence of user confidence.

(Robitza and Hlavacs, 2014) reported the effect of user confidence on the MOS using a video database. The user ratings were recorded using a tablet device, and authors claim to have maintained the viewing distance but viewing angle and other constraints were not addressed. A total of 27 subjects took part in the subjective assessment, and the results have shown a tendency of relatively high or low MOS for shorter rating times. In our analysis, the core of this study is based on the assumption that faster rating means that the user has higher confidence.

In the previous study (Minhas et al., 2019), we have observed a minor impact of user delight on MOS by the subjects. Although, this provided motivation for a detailed future work but due to the limited number of subjects in sub-categories, the results were not statistically significant. Moreover, the user mood levels were not taken into consideration.

3 OVERVIEW

In this section, we will provide a basic overview of the video streaming technologies used to obtain video stimuli for this paper. We will also highlight different QoE based metrics and subjective quality assessments for obtaining MOS.

3.1 Protocols and Codec for Video Streaming

The nature of live video streaming makes it more resilient to packet losses and traditional approach of RTSP/UDP/IP is the common technique to transmit video contents. The H.264/AVC codec is responsible for video presentation, coding, compression, decompression, etc. and is the most widely used video standard for online video delivery. The H.264/AVC codec is used for this paper due to its wide implementation, support and low computational requirements, which makes it suitable for the low cost devices. Although the latest H.265/HEVC is on the horizon, we used the old standard as our focus was primarily on effect of additional factors on the QoE. Moreover, this selection helped us to benchmark the results with previous studies.

3.2 A QoE Perspective

The QoE is focused on user perception of the service based on the quality of the shown content. Although, there is no general consensus on what actually is meant by QoE, there is a massive interest of service providers to gain insight about user perception towards their service. The methods used to quantize QoE are generally classified as objective and subjective where:

- Objective techniques assess the quality of a content, e.g. image or video, automatically and in full reference objective assessment the original reference image or video is compared with the image or video exposed to network artifacts and their subsequent structural effects like as brightness, contrast, blur, etc. Typical objective metrics are MSE, PSNR, SSIM and PEVQ (Opticom-GmbH, 2016).
- The subjective assessment is done by taking direct input from the user about a stimulus quality via conducting a survey. The MOS is normally obtained on a five-point Likert scale where a score of 5 means excellent. The important aspect is to make sure that the human subject's feedback is taken under well-defined repeatable conditions. The amount of time and money associated with these subjective assessments incline operators and service providers to go for objective metrics despite their shortcomings in number of scenarios for video delivery.

Thus, the QoE provides a holistic approach of service quality perceived from user standpoint, and this idea is supported by introducing a QoE hour glass model such as QoE=$f(QoS, QoP, QoD)$ (Minhas and Fiedler, 2013). In this model, QoE is defined as a composite function of traditional Quality of Service (QoS) metrics, Quality of Delivery (QoD) of the content and finally the Quality of Presentation (QoP).

(Reiter et al., 2014) have discussed that users might not be aware of the influence factors that affect their liking or disliking of a content. The physical, mental or current social state of a user may impact her behavior and corresponding decisions. Thus human based influence factors such as user mood, motivation or attention have a tendency to influence the QoE. They have also discussed the user frequency of using a system or a service as a temporal aspect that can influence the user perception. (Robitza and Hlavacs, 2014) have shown that confidence of a user plays a significant role in final MOS. Moreover, in our previous qualitative subjective assessments (Nawaz et al., 2014; Nawaz et al., 2017), we have noticed that videos with different spatial and temporal aspects may receive different MOS values, although the videos were streamed under identical network impairments. Moreover, from human IFs, we have observed the lack of focus and attention from subjects as normally the assessments were around 35 minutes long. We have also observed temporal factors that the users who are not acquainted with watching online content regularly, didn't bother too much about quality artifacts in general. Based on these findings, we carried out a research to choose a small set of video stimuli and record additional information from users regarding their liking of a particular video and frequency of the watching content as already discussed in the previous Section 2.

Table 1: Video Specification for streaming and subjective evaluation.

Parameters	H.264/AVC
Streaming Software	VLC Media Player
Frame Rate	25 fps
Duration	10–11 s
Profile	Main
Resolution	352×288

In this paper, we have extended our study and taken the user mood into account along with user delight and frequency of watching online content. The mood states are chosen from the *Circumplex Model of Affect* (Russell, 1980). The model shows that all human emotions arise from two fundamental neurophysiological states, i.e. pleasure and alertness. We have chosen excited, happy, relaxed and calm from the *Pleasant* axis. Although, excited and happy demonstrate high alert level as compared to the relaxed and calm, we have focused only on *Pleasant* and *Unpleasant* categories in this study. Tense, upset, bored, nervous and fatigues fall into the *Unpleasant* category as per the model. To incorporate the temporal aspects, each user was also asked about the frequency of watching online content at the start of the training session. The reason behind this selection is to benchmark the content delight for a particular video taken at the start of the session with corresponding MOS.

4 EXPERIMENTAL SETUP

The experimental setup used is based on an emulated network, and the reason for an emulated approach is tightly controlled network setup to replicate the real-world scenario exhibiting the actual impact of packet loss and other network artifacts along with the ability to repeat results under identical conditions. This hardware is already used in multiple experiments for different studies, and more details about hardware/software can be found in reference (Nawaz et al., 2014). The H.264/AVC streaming server was used to broadcast video streams using the VLC media player. The traffic shaper is a Linux based system with Netem emulation software for packet drop, delay, etc.

4.1 Video Selection

In order to stream videos over the experimental testbed, we have chosen three videos from xiph.org test media. The technical specifications of these videos are available in Table 1.

The choice of these videos is in-line with our previous studies as in order to evaluate the effect of additional factors at the user end, we need to compare the findings. This factor was foremost important to find any discrepancies in user ratings with additional factors in mind apart from the quality evaluation. The Football video involves the highest level of associated motion, but news is also considered fast in terms of temporal aspects. The Foreman, on the other hand, is regarded medium in both spatial and temporal domains, so the selection of video stimuli was in par with the specifications. It's important to mention that we have selected the lowest resolution QVGA that is available for both the high and low end smart phones. Due to low Internet speed in third world countries, this choice will result in decent video quality on low cost devices.

4.2 Network Impairments

As the focus of our study is on the validity of subjective quality assessment and corresponding MOS, so we have chosen seven packet loss scenarios ranging from 0.1% to 10% for streaming videos on the emulated setup. There was no delay or jitter associated with these videos during the experiment. The reason for this arrangement is to remain focused on qualitative measures but this choice resulted in output of a total of 21 streamed videos for the qualitative assessment.

4.3 Subjective Assessment

As we were analyzing various human factors like habits (frequency of watching online video clips), mood, delight (likeness) and their subsequent combinations so one set with a single QoS metric was selected. The videos were shown to the users as per the guidelines given in (ITU-R Rec. BT.500-10, 2012) regarding viewing distance and display characteristics. A training session was conducted before every assessment, and users were provided with both verbal and written instructions. The input was taken from the user regarding their frequency of watching online video clips with options to select among often, daily, sometime and never. The user's mood was also taken with the options of excited, happy, relaxed, calm, upset, bored, tense, fatigued and nervous. In the next step, test media without distortions was shown to the user, and they were asked whether they liked it or not based on a binary scale of 'Yes' and 'No'. The users were also requested to provide their ranking of the content based on their delight towards the shown content on the 1–9 scale, where 9 indicates the most delightful content. These ratings were scaled down to five-point scale with a step size of 0.5 using the formula $5-(9-R)/2$ where R stands for delight rating on the nine-point scale. This conversion helped us in comparing the effect of content delight with corresponding MOS. The user ratings for video quality were obtained using the Single-Stimulus method on a 5-point Absolute Category Rating (ACR) scale. The selection of test media for this paper meant a total of 24 videos, including the originals resulting in a total assessment time of around 10–12 minutes.

As a complement, we have used the PEXQ software (V1.3) to obtain objective metrics like PSNR and estimated subjective ratings, i.e. PEVQ MOS (Opticom-GmbH, 2016). In this paper, we have only used estimated PEVQ MOS ratings to compare with real MOS ratings obtained from the subjects.

5 RESULTS AND DISCUSSION

The results from the subjective assessment are reported in Table 2. A total of 64 participants rated the test media out of which three outliers were identified and subsequently removed. Out of the remaining 61 subjects, 40 males and 21 females participated with a mean age of 21.05 and mode 21. The MOS with 95% confidence intervals is calculated using the Student t-distribution, taking care of varying sample sizes. As there were multiple groups to test and in some categories, the number of subjects fell to single digit, we have calculated confidence intervals at a minimum of 10 subjects. We have also calculated one-way ANOVA using the SPSS software (IBM Corp., 2019) to determine the significance of the ratings among various categories with Tukey in case of significant values for Frequency and Mood. In general, we have observed that the majority of videos starts to show the freeze effect at a packet loss percentage of 1% or higher.

5.1 Impact of Delight of Shown Video Content

The average scores of content ratings on a five-point scale and MOS values for seven different packet loss ratios are shown in Figure 2.

The subjects that feel delighted on a binary scale by the content of video clips have rated the content high on the 9-point ordinal scale, which is an obvious choice. However, the important observation is the matched rating of the shown video stimuli with the overall MOS. We have calculated one-way ANOVA with α=0.05 and found *Foreman* videos at 1%, 5% and 10% packet loss ratio to have a p (significance) value of less than 0.05. The only other significant difference was observed in one *News* clip at packet loss percentage of 0.1%. So out of 21 video clips, where network artifacts have to be rated, we have noticed slight deviation in ratings for only 4 videos. Hence, we may conclude that in most cases, the users were able to accurately rate the stimuli regardless of their delight towards a particular content.

5.2 Impact of Frequency of Watching Online Video Content

The frequency of watching online content and its effect on content rating and average MOS are shown in Figure 3.

In one-way ANOVA analysis at significance level 0.05, we were unable to find a single user input including content rating where the output value is less than 0.05. The only ratings close to be significant are *Football* at 0.3% packet loss ratio with significance $p=0.056$ and *News* at 1% packet loss with the significance value of $p=0.090$ as shown in Table 3.

We observed a sample size of 37, 18, 6 for *Daily*, *Often* and *Sometime*, respectively. In order to get any statistical difference, we combined the *Often* and *Sometime* categories into a new *Not-Daily* category with a sample size of 24. Nevertheless, apart from *Football* at 0.3% packet loss ratio, we were unable to find any significant value to show any impact of the users' frequency of watching online content on MOS. Moreover, the ANOVA results from previous user group having three categories are completely random as compared to this new group and thus show no statistical difference in MOS as shown in Table 3.

These results clearly show that the user background of watching online videos daily, frequently or sometime hardly affects the user ratings, and these results are in line with our previous study (Minhas et al., 2019).

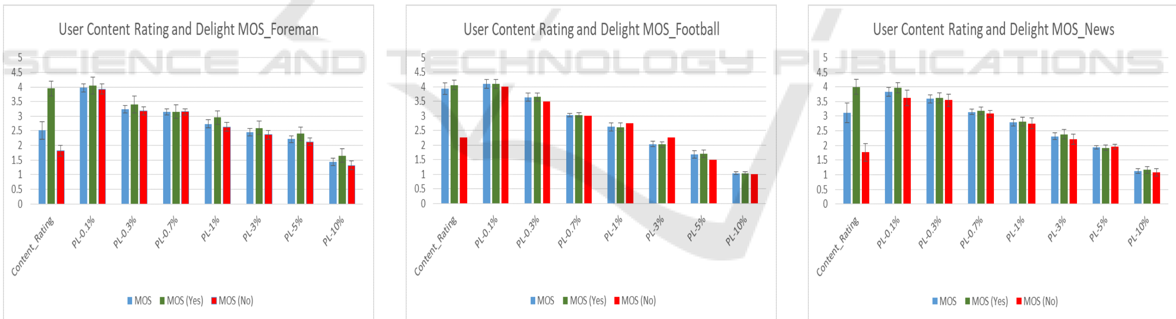
5.3 Impact of User Mood on Video Ratings and MOS

In case of user mood, we had only one sample of more than 10 subjects when the user is feeling *Calm*. So in order to do any interpretations of the available data, we aggregated the ratings from nine mood categories into two groups as already discussed in Section 4:

1. *Pleasant* which includes *Relaxed, Excited, Calm, Happy*;
2. *Unpleasant* which includes *Tense, Upset, Bored, Nervous, Fatigued.*

Table 2: MOS with 95% confidence intervals for different videos, categories and packet loss ratios (*PL*).

Video		Users	Content Rating	MOS_*PL* 0.1%	MOS_*PL* 0.3%	MOS_*PL* 0.7%	MOS_*PL* 1%	MOS_*PL* 3%	MOS_*PL* 5%	MOS_*PL* 10%
Foreman										
	All	61	2.52 ± 0.30	3.97 ± 0.15	3.25 ± 0.13	3.15 ± 0.10	2.74 ± 0.13	2.44 ± 0.13	2.21 ± 0.12	1.43 ± 0.13
Video Content Likeness	Yes	20	3.95 ± 0.25	4.05 ± 0.28	3.40 ± 0.28	3.15 ± 0.23	2.95 ± 0.24	2.60 ± 0.24	2.40 ± 0.24	1.65 ± 0.23
	No	41	1.82 ± 0.19	3.93 ± 0.18	3.17 ± 0.14	3.15 ± 0.11	2.63 ± 0.15	2.37 ± 0.15	2.12 ± 0.13	1.32 ± 0.15
Video Watching Frequency	Daily	37	2.69 ± 0.41	4.05 ± 0.21	3.29 ± 0.19	3.18 ± 0.13	2.78 ± 0.18	2.51 ± 0.17	2.22 ± 0.16	1.51 ± 0.17
	Often	18	2.19 ± 0.51	3.78 ± 0.27	3.22 ± 0.21	3.06 ± 0.21	2.56 ± 0.25	2.28 ± 0.23	2.17 ± 0.19	1.28 ± 0.23
	Sometime	6	2.42 (N/A)	4.00 (N/A)	3.00 (N/A)	3.17 (N/A)	3.00 (N/A)	2.50 (N/A)	2.33 (N/A)	1.33 (N/A)
User Mood	Pleasant	40	2.57± 0.37	3.98± 0.21	3.30± 0.18	3.23± 0.14	2.78± 0.17	2.53± 0.16	2.25± 0.16	1.48± 0.16
	Unpleasant	21	2.40± 0.54	3.95± 0.18	3.14± 0.16	3.00 ± 0.14	2.67 ± 0.22	2.29 ± 0.21	2.14 ± 0.16	1.33 ± 0.22
Football										
	All	61	3.94 ± 0.20	4.10 ± 0.15	3.64 ± 0.14	3.03 ± 0.07	2.62 ± 0.15	2.03 ± 0.09	1.69 ± 0.13	1.03 ± 0.05
Video Content Likeness	Yes	57	4.06 ± 0.17	4.11 ± 0.15	3.64 ± 0.15	3.03 ± 0.07	2.61 ± 0.16	2.02 ± 0.10	1.70 ± 0.13	1.04 ± 0.05
	No	4	2.25 (N/A)	4.00 (N/A)	3.50 (N/A)	3.00 (N/A)	2.75 (N/A)	2.25 (N/A)	1.50 (N/A)	1.00 (N/A)
Video Watching Frequency	Daily	37	4.01 ± 0.28	4.00 ± 0.16	3.51 ± 0.19	3.00 ± 0.08	2.62 ± 0.20	2.05 ± 0.13	1.70 ± 0.17	1.03 ± 0.06
	Often	18	3.72 ± 0.36	4.28 ± 0.33	3.89 ± 0.23	3.11 ± 0.16	2.67 ± 0.30	2.00 ± 0.17	1.72 ± 0.23	1.06 ± 0.12
	Sometime	6	4.17 (N/A)	4.17 (N/A)	3.67 (N/A)	3.00 (N/A)	2.50 (N/A)	2.00 (N/A)	1.50 (N/A)	1.00 (N/A)
User Mood	Pleasant	40	3.98 ± 0.27	4.05 ± 0.19	3.58 ± 0.18	3.03 ± 0.09	2.63 ± 0.19	2.05 ± 0.12	1.63 ± 0.17	1.03 ± 0.05
	Unpleasant	21	3.88 ± 0.30	4.19 ± 0.23	3.76 ± 0.24	3.05 ± 0.10	2.62 ± 0.27	2.00 ± 0.14	1.81 ± 0.18	1.00 ± 0.00
News										
	All	61	3.12 ± 0.34	3.84 ± 0.15	3.59 ± 0.14	3.15 ± 0.09	2.79 ± 0.12	2.31 ± 0.12	1.93 ± 0.06	1.13 ± 0.09
Video Content Likeness	Yes	37	4.00 ± 0.25	3.97 ± 0.17	3.62 ± 0.18	3.20 ± 0.13	2.81 ± 0.15	2.38 ± 0.16	1.92 ± 0.09	1.16 ± 0.12
	No	24	1.77 ± 0.30	3.63 ± 0.27	3.54 ± 0.21	3.08 ± 0.12	2.75 ± 0.19	2.21 ± 0.18	1.96 ± 0.09	1.08 ± 0.12
Video Watching Frequency	Daily	37	3.09 ± 0.47	3.81 ± 0.19	3.54 ± 0.19	3.14 ± 0.12	2.76 ± 0.15	2.27 ± 0.15	1.95 ± 0.08	1.19 ± 0.13
	Often	18	2.97 ± 0.58	3.83 ± 0.30	3.67 ± 0.24	3.11 ± 0.16	2.72 ± 0.23	2.33 ± 0.24	1.94 ± 0.12	1.00 (N/A)
	Sometime	6	3.75 (N/A)	4.00 (N/A)	3.67 (N/A)	3.33 (N/A)	3.17 (N/A)	2.50 (N/A)	1.83 (N/A)	1.17 (N/A)
User Mood	Pleasant	40	3.11 ± 0.45	3.78 ± 0.20	3.58 ± 0.18	3.15 ± 0.12	2.75 ± 0.16	2.33 ± 0.15	1.98 ± 0.05	1.18 ± 0.12
	Unpleasant	21	3.14 ± 0.53	3.95 ± 0.23	3.62 ± 0.23	3.14 ± 0.16	2.86 ± 0.16	2.29 ± 0.21	1.95 ± 0.10	1.05 ± 0.10



(a) Foreman (b) Football (c) News

Figure 2: User Video Ratings and MOS (Delight): (a) Foreman (b) Football (c) News.

This approach gave us a sample size of 40 and 21 subjects, respectively. The effect of the user mood state on the MOS is shown in Figure 4.

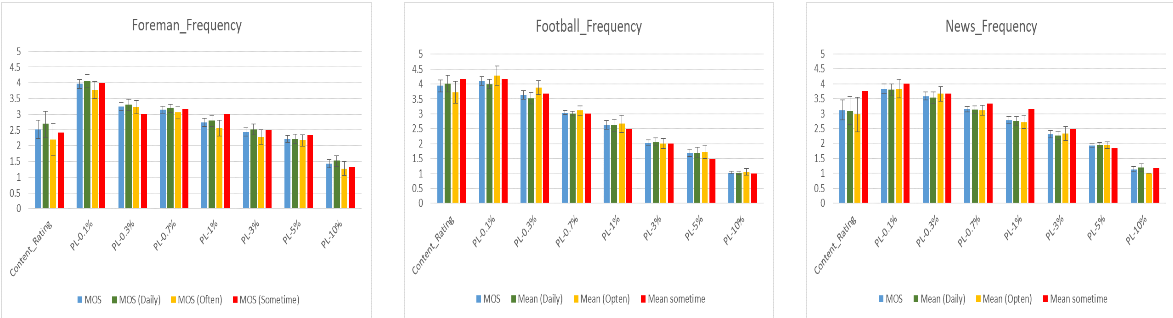
Table 3: Oneway ANOVA of User Frequency.

Video and Loss%	Significance Level: 0.05 Freq. (3 cat.)	 Freq. (Not-/Daily)
Foreman 10%	0.233	0.090
Football 0.1%	0.228	0.094
Football 0.3%	0.056	0.025
News 1%	0.090	0.522

Table 4: Oneway ANOVA of User Mood.

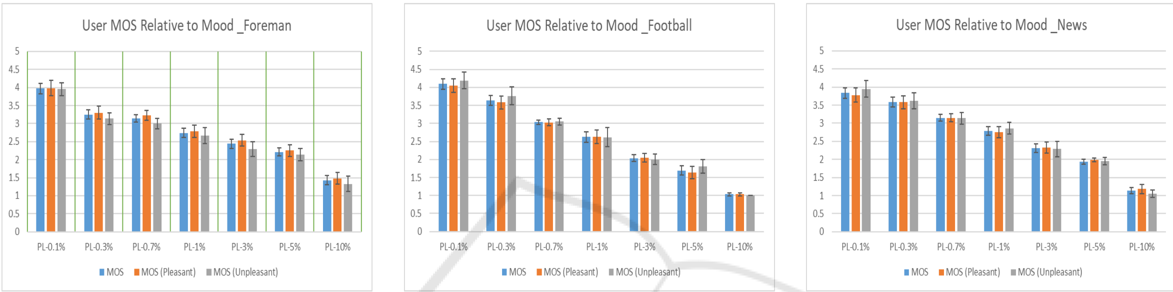
Video and Loss%	Significance Level: 0.05 Mood (Pleasant, Unpleasant)
Foreman 0.7%	0.036
Foreman 3%	0.076

We can observe a slight impact on almost all stimuli but the effect in not pronounced. Moreover, the results from ANOVA test showed that there is only one stimulus in the significant range as shown in the Table 4.



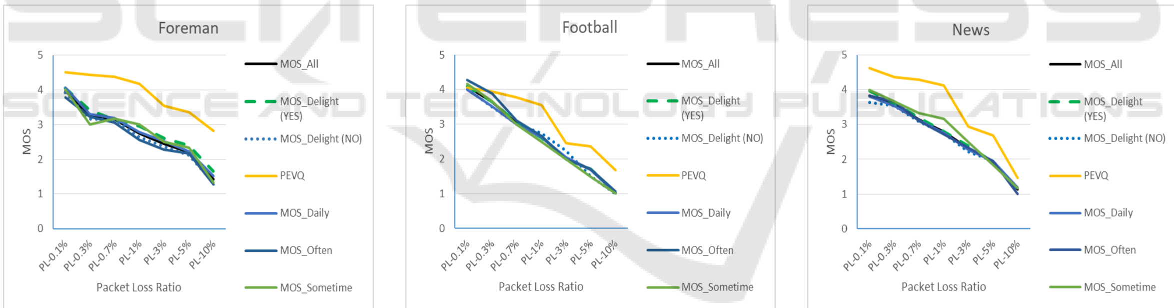
(a) Foreman (b) Football (c) News

Figure 3: User Video Ratings and MOS (Frequency): (a) Foreman (b) Football (c) News.



(a) Foreman (b) Football (c) News

Figure 4: MOS in Relevance to Mood: (a) Foreman (b) Football (c) News.



(a) Foreman (b) Football (c) News

Figure 5: User and PEVQ ratings: (a) Foreman (b) Football (c) News.

The subjects in the group *Pleasant* have given better MOS ratings as compared to *Unpleasant* with a mean difference of 0.23 for *Foreman* stimulus at 0.7% packet loss ratio. The only other scenario closed to be significant is *Foreman* at 3% packet loss ratio. This tentatively suggests that there is a slight effect of mood on MOS ratings, but subjects are able to identify the quality aspects irrespective of their state of mind.

5.4 PEVQ MOS Benchmarks

Finally, the comparison of MOS values calculated by the PEXQ software (V1.3) (Opticom-GmbH, 2016) with actual MOS values of human subjects is shown in the Figure 5. The subjects' ratings were uniform despite their differences in terms of delight, mood or frequency, and the difference from PEVQ based ratings is apparent. In our cases, PEVQ tends to overestimate the video quality as compared to real human subjects, which is in line with a previous study (Nawaz et al., 2014). The offset between PEVQ and actual ratings is consistent, although not constant, for almost all the videos. This potential behaviour should be kept in mind when using PEVQ for quality evaluation.

6 CONCLUSION

In this paper, we have considered additional factors like content delight, frequency of watching online video content and user mood and their impact on MOS for multimedia communication. The video stimuli were streamed in different packet loss scenarios, and we have used both binary and ordinal scale to take account of the user delight. We have seen a slight impact of both frequency of using online video content or mood on MOS, but the results are not statistically significant. On the other hand, we have observed a slight tendency to give higher MOS ratings to stimuli where the user is delighted to watch content, but the different is not too large. It is important to mention that all subjects were technologically aware of the field, and we might get more relevance from the diverse set of users in an additional study. The results establish the effectiveness of MOS ratings obtained through subjective assessments for video clips. Finally, we have benchmarked the subjective MOS ratings with PEVQ MOS and observed the software tendency to overestimate the quality of the streamed videos. This paper motivates to test effectiveness of the results by using latest codecs with high resolution videos streamed over high-speed networks in future work.

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