Scientific Journals
of the Maritime University of Szczecin

Zeszyty Naukowe
Politechniki Morskiej w Szczecinie

2024, 79 (151), 30–38
ISSN 2392-0378 (Online)
DOI: 10.17402/613

Received: 15.05.2024
Accepted: 26.07.2024
Published: 30.09.2024

Subjective quality evaluation of 8- and 10-bit MP4-coded video sequences from Netflix

Przemysław Falkowski-Gilski[1]✉, Tadeus Uhl[2], Parameshachari Bidere Divakarachari[3]

[1] https://orcid.org/0000-0001-8920-6969
[2] https://orcid.org/0000-0001-6849-9168
[3] https://orcid.org/0000-0002-3997-5070

[1] Gdansk University of Technology, Faculty of Electronics, Telecommunications and Informatics, Poland
[2] Flensburg University of Applied Sciences, Germany
[3] Nitte Meenakshi Institute of Technology, Bengaluru, India
e-mail: [1]przemyslaw.falkowski@eti.pg.edu.pl; [2]tadeus.uhl@hs-flensburg.de, [3]paramesh@nmit.ac.in
✉ corresponding author

Keywords: coding, compression, QoE (Quality of Experience), UX (User Experience), video content, Netflix
JEL Classification: C63, C83, C88, C93

Abstract
Recently, many researchers have been intensively conducting quality of service (QoS), quality of experience (QoE), and user experience (UX) studies in the field of video analysis. This paper is intended to make a new, complementary contribution to this field. Currently, streaming platforms are key products in relation to delivering video content online. Most often, they include the MP4 video format, which is most widely utilized among audio-visual codecs. This study involves a group of 38 individuals, aged between 21–35 years old, in a laboratory consisting of 20 iMacs with 4K retina display. The presented signal sequences included content sourced from the Netflix Chimera repository, with 8- and 10-bit depth, available in different resolutions of 270p, 432p, 720p, and 1080p. Tests included a subjective quality evaluation in a 5-step mean opinion score (MOS) scale, focused on the UX aspect. According to the obtained results, content with the lowest and highest resolutions is optimal in 8-bit depth, while movies with intermediate resolutions are better in 10-bit depth. For 8-bit content, the main problem is pixelation, whereas, in the case of 10-bit samples, the main issue is color noise, particularly in the case of the lowest resolution. Many viewers indicated that 10-bit encoding offered lower quality. Moreover, 8-bit movies caused a lower quality of the gradient, presumably due to the smaller range of the available color. However, 8-bit movies in the same situation generate visible stripes on static images in the background, causing a lower quality of the gradient, which is probably due to the smaller range of available colors. The results of the performed experiments may be of particular interest to content creators and distributors, particularly network and cable operators, as well as wireless and wired providers.

Introduction

In the opinion of many people, the most important parameter in relation to video content is increased image resolution since it provides the most visible results (Falkowski-Gilski & Uhl, 2020). It becomes an even more important aspect for cable and network operators with respect to network throughput prediction, including 5G, as well as adaptive mobile solutions (Biernacki, 2024). Watching movies and TV shows, even with subtitles, is a basic everyday activity. A variety of evolving factors relating to technological advances, cinema production, and social behavior challenge our perception and understanding. In the study of Becerra et al. (Becerra et al., 2024), the authors seek to formalize and provide context to these influential factors under a wider and novel term referred to as dialogue understandability. They propose a working definition, which is a listener's capacity to follow the story without undue cognitive effort or concentration being required that impacts their quality of experience (QoE). This paper identifies, describes, and categorizes the factors and then explores available measurement tools in the literature and links them to the factors they could potentially be used for. The maturity and suitability of these tools are evaluated using a set of pilot experiments.

The scale of the online video platform industry is growing rapidly, and with the increase in the number of such platforms, the competition is becoming more intense. A previous study (Ying Jie, Kee & Omar, 2023) examined the factors that influence willingness to pay on the Tencent video platform. It draws upon the theory of planned behavior and other relevant concepts, i.e., perceived value, perceived usefulness, perceived playability, perceived quality, and copyright awareness. This study aims to develop a conceptual model to determine the influence of psychological and individual aspects on the willingness to pay among video users. The results indicate that the theoretically assumed path relationships were consistent with the actual measured data. There were significant relationships between user attitudes, subjective norms, perceived behavioral control, perceived usefulness, perceived value, perceived playfulness, perceived quality, copyright awareness, and willingness to pay.

Generally speaking, mobile cloud computing (MCC) is one of the most visible efforts to launch computing technology beyond the use of tools and achieve universal acceptance. It has become increasingly important in people's daily lives, highlighting the urgent need for new approaches. The motivation of mobile users and the nature of cloud computing make it ideal for developing various services. The focus of another paper (Mirusmonov et al., 2023) was on the cognitive, social, and technical motivations that mobile users experience when owning, interacting with, and using mobile devices through MCC. These authors also explored the moderating role of network externalities between perceived utility, usage attitudes, and actual use. The results showed that the positive effects of perceived utility and attitudes on mobile cloud computing usage increase gradually with network externalities. This study provides a theoretical basis for academics and practical guidance for service providers to promote MCC.

The market, tests, and quality evaluation

In today's fiercely competitive markets, customers' desire for instant gratification has shifted toward subscription video-on-demand (SVOD) services as the preferred choice for digital entertainment. Moreover, as viewers increasingly abandon traditional broadcast TV, the billion-dollar market for SVOD is projected to expand further. A paper by Badr, Sharaf, and Mahrous (Badr, Sharaf & Mahrous, 2024) aimed to analyze the market dynamics and explore expansion opportunities in the SVOD industry. By presenting a comprehensive overview of the global streaming market, it emphasizes the pivotal role of customer choice and incorporates the perspectives of content creators. It also highlighted the significance of financial analysis in understanding the complex landscape of streaming services.

As is well-known, a codec is the most important element of any streaming application, such as Netflix or YouTube, but its complexity increases with its advancement. The high-efficiency video coding (HEVC) codec selects an intra-mode out of a total of 35 intra-modes using the brute-force method. In the study of Tariq et al. (Tariq et al., 2024), the authors utilized a spiral optimization algorithm (SOA) to overcome the aforementioned limitation of HEVC. Firstly, the elements of SOA are efficiently mapped to the elements of HEVC. Secondly, the current best intra-mode becomes the center of the spiral of SOA. Thirdly, the current best intra-mode is considered optimal if the spiral completes three spiral loops and the current intra-mode still remains the best. Otherwise, the new optimal intra-modes become the center of the spiral.

Spatial information (SI) and temporal information (TI) have been used widely as an approximate estimation of video complexity. Recently, they have found use in many other applications, such as QoE modeling, bandwidth, and rate-distortion modeling, for both traditional and non-traditional (including gaming and dynamic vision sensors) videos. It is often assumed that SI and TI only depend on video content while, in fact, factors such as resolution, bit depth, and compression have an impact on the values of SI and TI for specific video content. A systematic study on SI and TI for videos that investigates the effect of different video encoding and processing steps on SI and TI values has been missing so far. Moreover, SI and TI calculations have been limited to 8-bit videos, while there has been increasing popularity and usage of 10-bit videos. Toward this end, Barman, Khan, and Martini (Barman, Khan

& Martini, 2019) present a comprehensive evaluation of the variation of SI and TI for different 8- and 10-bit videos. Results and insights into the variation of SI and TI values for different encoding settings, choice of encoders, temporal pooling methods, resolution, etc., are also presented.

Another paper (Topiwala, Krishnan & Dai, 2018) presented a study comparing the coding efficiency performance of three video codecs: versatile video coding (VVC) benchmark set 1 (BMS1), AV1 codec of the Alliance for Open Media (AOM), and HEVC main profile reference software. Two approaches to coding were used, i.e., constant quality (QP) and target bit rate (VBR). Constant quality encoding was performed with all three codecs for an unbiased comparison of the core coding tools. Whereas target bitrate coding was undertaken with the AV1 codec to study the compression efficiency achieved with rate control, which can and does have a significant impact. Performance was tabulated on two fronts, namely, objective performance based on PSNRs and an informal subjective assessment. The general conclusion derived from the assessment of objective metrics and subjective evaluation was that VVC (BMS1) appeared to be superior to AV1 and HEVC under both constant quality and target bitrate coding constraints. AV1 showed superior coding gains with respect to HEVC under target bitrate coding, but, in general, it had increased computational complexity and, hence, an encode time factor of 20–30 over HEVC.

The rise of Internet services in recent years, especially the flourishing development of new social platforms, such as Taobao Live, TikTok, Huya, YouTube, and Twitch, has led to a significant increase in Internet video services. For example, YouTube Live stats revealed that 2020 was the largest year ever for Gaming Live, with 100 billion watch time hours. As a result, the entire network communication model has gradually evolved into a livecast computing network (LCN) architecture, where various network units involved in Internet live video services, with their computing, storage, distribution, and transmission capabilities, form an architecture that can meet high concurrency and low latency requirements. A previous article (Zeng et al., 2023) investigated, sorted, and analyzed LCN architecture relating to standards, protocols, and network model solutions from the perspective of Internet live video services. Firstly, it outlined the standards, system architecture, and main streaming media protocols of Internet live video. Secondly, it analyzed the video algorithm network architecture models, including cloud-based, edge-based, and cloud-network-edge collaborative models. Finally, it summarized the main challenges and research directions faced by video algorithm networks in the future. Additional comments on QoS, QoE, and network quality evaluation studies may be found in numerous previous works (Nowicki & Uhl, 2017; Falkowski-Gilski, 2023; Falkowski-Gilski & Uhl, 2023; Zmyslowski, Kelner & Falkowski-Gilski, 2023).

Materials and methods

The subjective user experience (UX) part of this study was performed according to ITU-T Rec. BT.500-14 (ITU-T, 2019) on an Intel Core i7 iMac with a 21.5-inch 4K Retina (4096×2304 pixels) display. The group of viewers consisted of 38 individuals aged between 21–35 years old.

Test equipment and participating individuals

The laboratory class included 20 iMac stands, as in a previous study (Falkowski-Gilski, Uhl & Hoppe, 2024), which enables the evaluations to be carried out simultaneously on a wider group of individuals. The whole campaign was performed over a single week. Users were asked to provide a score in a standard 5-step mean opinion score (MOS) scale, from 1 (bad quality) to 5 (excellent quality), as well as feedback and comments with respect to consumed content. The test included two groups of people with different ages and backgrounds, as shown in Table 1.

Table 1. Individuals participating in the study

Group no.	Number of individuals	Age (years old)	Description
1	10	21–24	Full-time B.Sc. and M.Sc. students
2	28	25–35	Part-time M.Sc. students

Each person undertook the training phase before beginning the essential study, during which they could adjust the stand and viewing angle, as well as the screen brightness level of the display, according to their own preferences. This was performed in order to best meet their everyday settings based on each individual's background and previous experience.

Video samples

The processed video content included four files for each bit depth, as described in Table 2, including eight samples presented in a randomized way in full-screen mode. Each video sample was composed of five sequences that were a couple of seconds in length, as described in Table 3.

Table 2. Tested video samples

File name	Bit depth	Resolution (pixels)	Bitrate (kbps)
Video 1	8-bit	480×270	552
Video 2	8-bit	768×432	1160
Video 3	8-bit	1280×720	3363
Video 4	8-bit	1920×1080	6736
Video 5	10-bit	480×270	531
Video 6	10-bit	768×432	1090
Video 7	10-bit	1280×720	2380
Video 8	10-bit	1920×1080	6191

Table 3. Analyzed video sequences

Sequence no.	Description
1	Walk like a man
2	Windmill
3	Traffic
4	Toddler fountain
5	Toddler montage

There was a short break between switching from one resolution to another so that the users could write down their comments. Of course, no one was informed about the resolution, bitrate, or other parameters of the currently evaluated video content. For the purpose of this study, the presented MP4 files were anonymized and only labeled as Video 1–8. All of them were sourced from the Chimera Netflix repository (Netflix, 2024).

Results

The overall subjective MOS results, including all eight video files, as well as age groups ranging from 21–35 years old, are shown in Figures 1–8. Video sequences for the 8-bit depth are shown in Figures 1–4, whereas those for the 10-bit depth are shown in Figures 5–8, respectively.

All the obtained data were processed using the analysis of variance (ANOVA) statistical method, with the confidence level set at 0.95. It is noteworthy that the obtained confidence intervals for measured parameters were always less than 10 % of their average values. This proves that a sufficiently large number of measurements have been made in order to treat the obtained results as reliable.

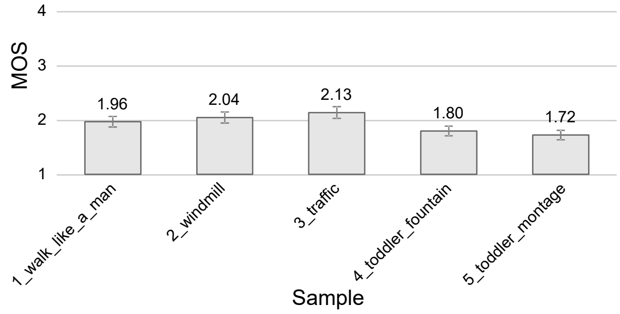

Figure 1. Subjective results for all age groups – Video 1 file

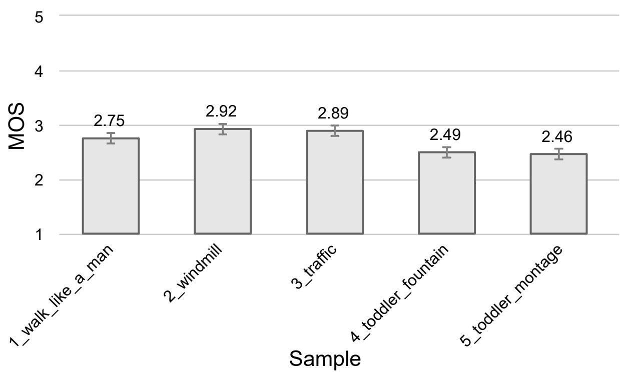

Figure 2. Subjective results for all age groups – Video 2 file

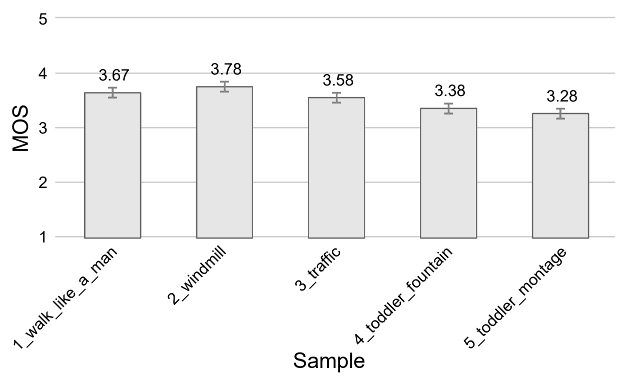

Figure 3. Subjective results for all age groups – Video 3 file

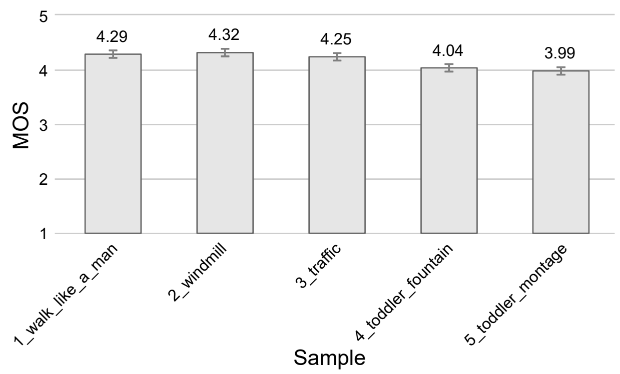

Figure 4. Subjective results for all age groups – Video 4 file

Figures 1–4 show a clear increase in the ratings of watched video sequences as the image resolution and bit rate grew. There is a rule here: the greater the amount of information contained in the transmitted video, the higher the assessment of the test subjects.

When watching a video in 8-bit depth, the main problem was pixelation of the image due to the low resolution itself. This had the greatest effect on the judgment of sequences with small objects, such as drops from a fountain or windmills, but was less noticeable in scenes with fast-moving objects, such as cars on a highway, because a person needs little detail to see a familiar object and not very high quality if it moves quickly and only stays on screen for a fraction of a second. Interestingly, increasing the resolution from 480p to 768p and the bitrate by almost two times did not have a major impact on the highway scene, but significantly improved the experience of watching a video with a walking person. Videos with a huge number of moving small objects (like water drops) looked poor, even in full HD. To summarize, it seems that the minimum acceptable resolution is 1280×720.

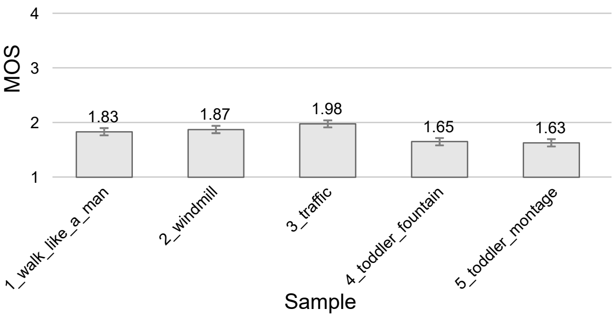

Figure 5. Subjective results for all age groups – Video 5 file

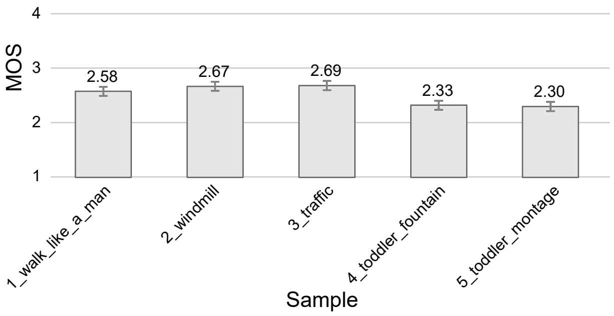

Figure 6. Subjective results for all age groups – Video 6 file

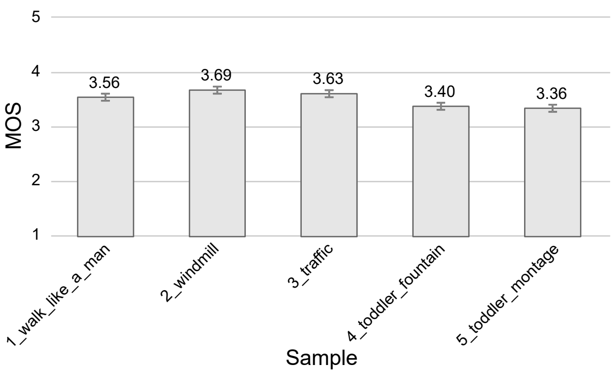

Figure 7. Subjective results for all age groups – Video 7 file

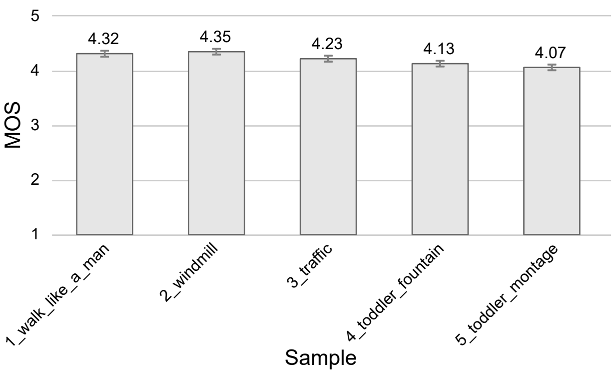

Figure 8. Subjective results for all age groups – Video 8 file

The QoE plots in Figures 5–8 are very similar to the results presented in Figures 1–4. Only at a low resolution and a low video transmission speed is a worse evaluation noticeable for 10-bit sequences compared to 8-bit sequences.

When watching videos in 10-bit depth, the main problem of low resolution was color noise, which was very noticeable at a low pixel density and was most strongly expressed in the case of shadows, bright and monotonous colors, and static objects. This artifact significantly worsened the impression of watching the video of the highway because all static objects were clearly distorted. This artifact disappeared once sufficient pixel density was achieved (i.e., higher than 1280×720) and resulted in significant improvements in video transmission and smoothness. Some artifacts were still visible but only in dark places.

In high resolutions and scenes with fast objects, such as cars, water drops, and windmills, the main factor lowering the overall high-resolution score was the frame rate. Only 24 frames per second was not enough for active scenes where objects noticeably started to move discontinuously, but not so significantly for calm scenes such as a person walking.

Discussion

Next, we performed an analysis of MOS scores for particular age groups: Group 1 (21–24 years old) and Group 2 (25–35 years old).

Results for Group 1

Subjective scores for the second group (older, part-time M.Sc. students) are shown in Figures 9–16, whereas those for the 8-bit depth are displayed in Figures 9–12. Those for the 10-bit depth are shown in Figures 13–16.

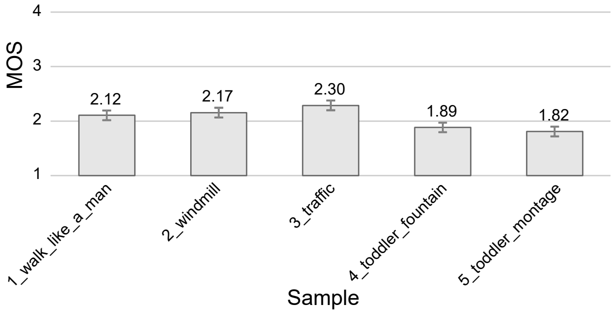

Figure 9. Subjective results for Group 1 – Video 1 file

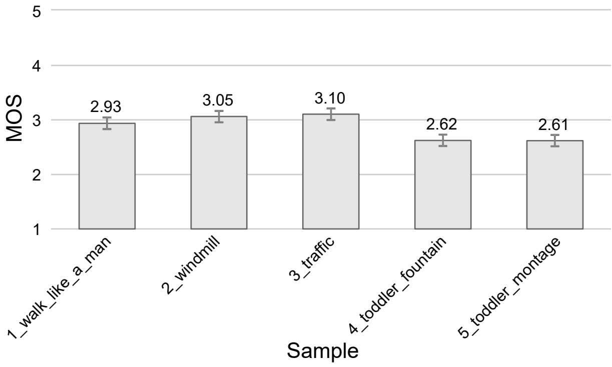

Figure 10. Subjective results for Group 1 – Video 2 file

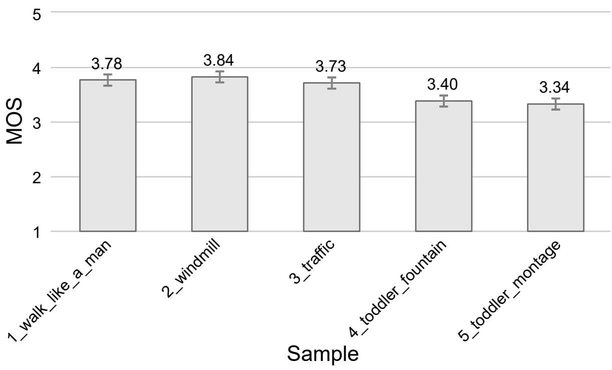

Figure 11. Subjective results for Group 1 – Video 3 file

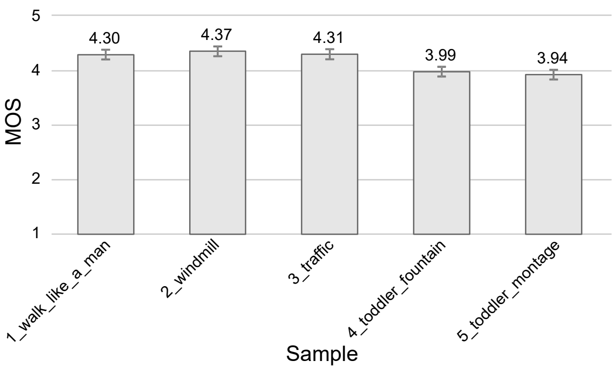

Figure 12. Subjective results for Group 1 – Video 4 file

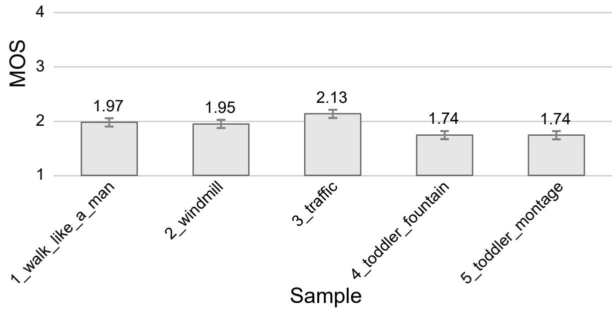

Figure 13. Subjective results for Group 1 – Video 5 file

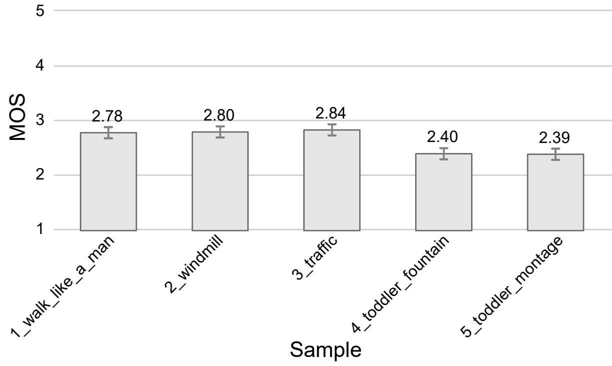

Figure 14. Subjective results for Group 1 – Video 6 file

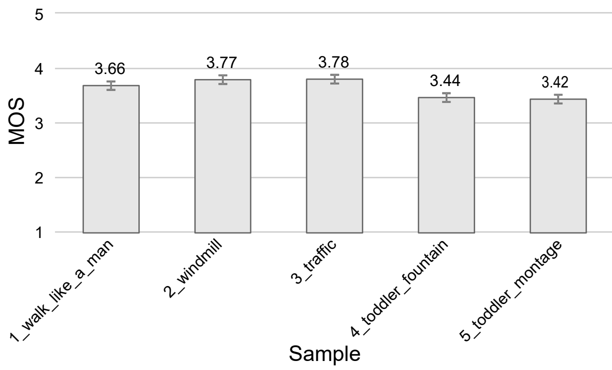

Figure 15. Subjective results for Group 1 – Video 7 file

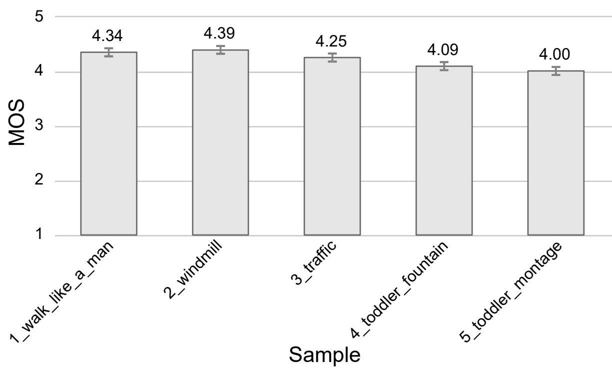

Figure 16. Subjective results for Group 1 – Video 8 file

The test results shown in Figures 9–16 display a similar course to those in the 21–35 years old age group. Only with a lower image resolution one can notice a slightly better rating. There is a possibility that the group of younger test subjects does not yet have as much experience with multimedia applications as the group of more mature people.

The ratings for individual videos with 8- and 10-bit encoding are almost identical, which may suggest that this factor does not matter much when consuming such content. In both cases, one can notice a significant leap in the rating when traversing from 480×270 to 1280×720 resolution. In this case, the greatest increase in quality and decrease in image pixelation can be seen, while a further increase in subjective MOS scores in relation to image quality seems to be logarithmic, i.e., subsequent increases in resolution have little impact on the change in the rating. The video with a toddler received the lowest average ratings due to the fact that there are many small particles (water) in it, which negatively affect the overall image quality.

It is expected that 10-bit encoding should offer greater color richness due to the use of more data to store a single color. When comparing movies with the same resolution, many people indicated that movies with 10-bit encoding were of lower quality. The difference was most noticeable in low-resolution videos. Videos with a higher encoding mode were grainier. Perhaps this effect was not related to the encoding but to the bitrate. The evaluated 10-bit movies had a lower bitrate, even though this method of encoding requires more data, potentially resulting in lower quality for movies of the same length and resolution. This is probably an effect of increased compression, given that, despite the higher encoding, the mere file size differences were not significant.

Results for Group 2

Subjective scores for the second group (older, part-time M.Sc. students) are shown in Figures 17–24, whereas those for the 8-bit depth are displayed in Figures 17–20 and those for the 10-bit depth are shown in Figures 21–24. As proven during the preliminary phase, these people tend to consume audio-visual content much more often than the younger group (full-time B.Sc. and M.Sc. students) and are keener on technology. Furthermore, they are more eager to pay for higher quality content, as most of them are subscribed to at least one of the popular streaming platforms.

The results shown in Figures 17–24 confirm the hypothesis that the group of more mature test subjects evaluates video sequences more critically compared with the group of younger people. This is especially visible when evaluating low-resolution video sequences. The more mature group of viewers often pays for access to multimedia resources and are, therefore, more critical of the quality of services provided to them.

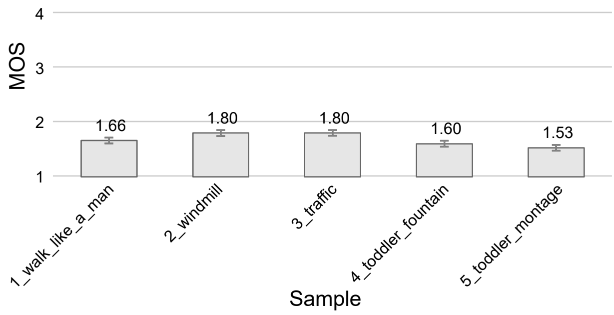

Figure 17. Subjective results for Group 2 – Video 1 file

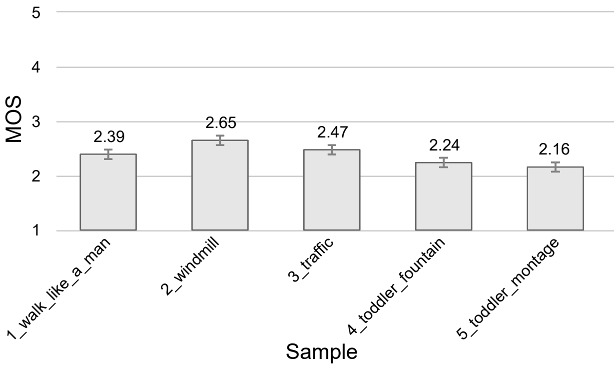

Figure 18. Subjective results for Group 2 – Video 2 file

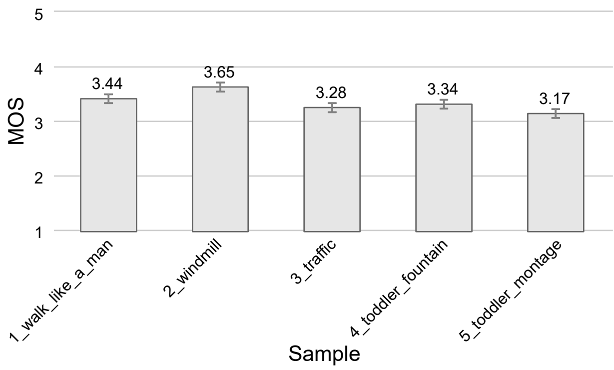

Figure 19. Subjective results for Group 2 – Video 3 file

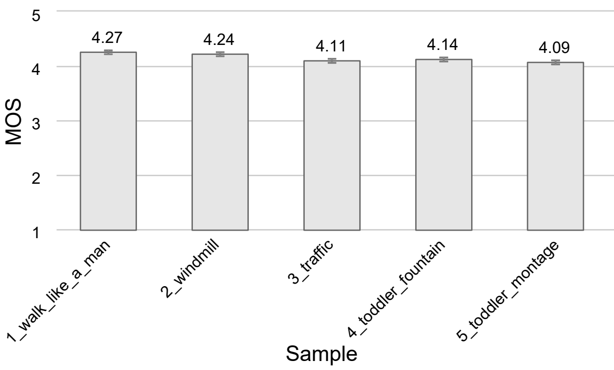

Figure 20. Subjective results for Group 2 – Video 4 file

According to the viewers, 8- and 10-bit movies generally do not present a clear difference. Interestingly,

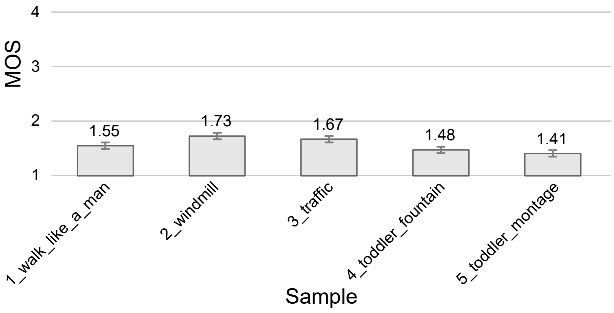

Figure 21. Subjective results for Group 2 – Video 5 file

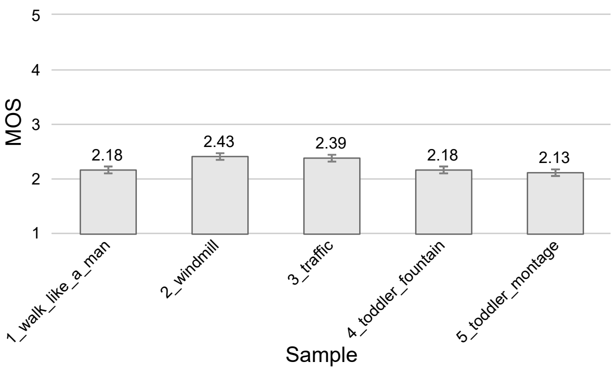

Figure 22. Subjective results for Group 2 – Video 6 file

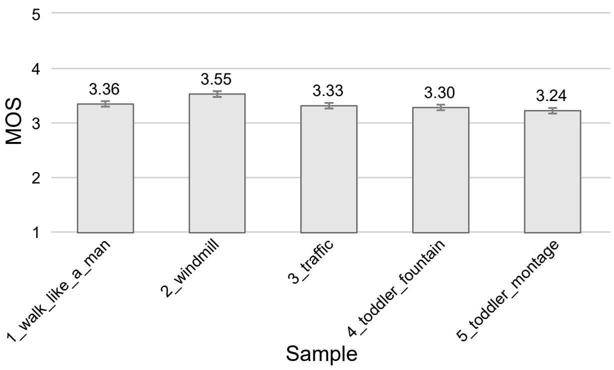

Figure 23. Subjective results for Group 2 – Video 7 file

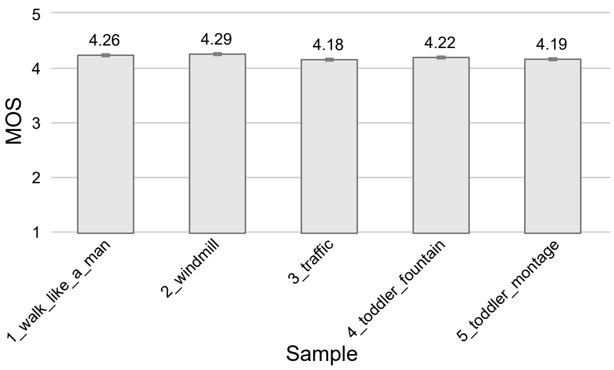

Figure 24. Subjective results for Group 2 – Video 8 file

content that has high dynamics in the foreground and is converted in a 10-bit depth generates a slight noise on static images in the background. However, 8-bit movies in the same situation generate visible stripes on static images in the background, causing a lower quality of the gradient, which is probably due to the smaller range of available colors.

Conclusions

Generally speaking, the conclusions of this study can be summarized in the following way. Obviously, content with higher resolution simply looks better, as the difference between 270p and 432p files was noticeably higher than between 720p and 1080p files. Content with fast-moving elements (windmills, cars, or water) was rated worse due to their low number of frames per second (FPS).

Next, files with 10-bit encoding, especially at lower resolutions, proved to be of lower quality than files with 8-bit encoding because of the noticeable graininess. Nevertheless, they were smaller in size. Furthermore, there was no perceived difference in color reproduction for files with 8- and 10-bit encoding. Additionally, in relation to higher video resolutions, scores for both bit depths were quite similar.

To summarize, movies in 8- and 10-bit depths are similar at all resolution levels. However, there are slight differences between them. It is noteworthy that content with the lowest and highest resolutions is better in 8-bit depth, while movies with intermediate resolutions are optimal in 10-bit depth. Purely theoretically, the image in the 10-bit depth should be better, but most likely, due to double conversion, the image remains distorted.

According to the obtained results, the group of more mature viewers (25–35 years old) evaluated video sequences more critically than the younger group (21–24 years old). This was especially visible when evaluating low-resolution video sequences. Additionally, the more mature group often paid for access to multimedia resources and was, therefore, more critical of the quality of services provided to them. In the future, it would be interesting to compare the obtained results with those from an objective metric such as the peak signal-to-noise ratio (PSRN) or structural similarity index (SSIM) (Ruiz et al., 2013).

In the opinion of many students, the optimal resolution for such a display would be 1080p or 1440p. Of course, there are many mobile devices with even smaller screen sizes that offer resolutions higher than full HD, with refresh rates above 60 FPS. It is worth pointing out that, for many of the participating individuals, higher refresh rates and FPS would be more effective. This becomes an important aspect when watching any kind of real-time online streamed or buffered video content, especially on mobile terminals that offer a refresh rate of 120 FPS and higher.

As pointed out by many, 4K resolution would work better on a screen with a larger diagonal size. Probably, even in the case of native 4K content, the difference with full HD would be small or even unnoticeable to most people if they were not informed about the difference in parameters in advance. Nevertheless, 4K and even 8K TV screens that are 65+ inches across the diagonal are becoming increasingly affordable. Even though gaming consoles support 4K resolutions, this is most often only in an upscaling mode. It seems that the future of image resolution is strongly connected with consoles and gaming, including both portable and domestic consumer devices. Therefore, it would also be interesting to broaden the type, as well as the resolution and file format of the evaluated content, on a wider range of consumer devices, including handhelds and other terminals.

References

1. Badr, N., Sharaf, S. & Mahrous, A.A. (2024) Streaming wars: an analysis of the growth and competitive landscape of the subscription video-on-demand services market. *EuroMed Journal of Management* 6 (1), pp. 23–41, doi: 10.1504/EMJM.2024.135992.
2. Barman, N., Khan, N. & Martini, M.G. (2019) Analysis of spatial and temporal information variation for 10-bit and 8-bit video sequences. *IEEE 24th International Workshop on Computer Aided Modeling and Design of Communication Links and Networks* (*CAMAD*), Limassol, Cyprus, pp. 1–6, doi: 10.1109/CAMAD.2019.8858486.
3. Becerra, H., Ragano, A., Debnath, D., Ullah, A., Lucas, C.R., Walsh, M. & Hines, A. (2024) Dialogue understandability: Why are we streaming movies with subtitles? doi: 10.48550/arXiv.2403.15336.
4. Biernacki, A. (2024). Throughput prediction of 5G network based on trace similarity for adaptive video. *Applied Sciences* 14 (5), 1962, doi: 10.3390/app14051962.
5. Falkowski-Gilski, P. (2023) Audio content and crowdsourcing: A subjective quality evaluation of radio programs streamed online. *19th EAI International Conference* (*MobiQuitous*).
6. Falkowski-Gilski, P. & Uhl, T. (2020) Current trends in consumption of multimedia content using online streaming platforms: a user-centric survey. *Computer Science Review* 37 (4), 100268, doi: 10.1016/j.cosrev.2020.100268.
7. Falkowski-Gilski, P. & Uhl, T. (2023) Comparing apples and oranges: A mobile user experience study of iOS and Android consumer devices. *19th EAI International Conference* (*MobiQuitous*).
8. Falkowski-Gilski, P., Uhl, T. & Hoppe, C. (2024) User experience evaluation study on the quality of 1K, 2K, and 4K H.265/HEVC video content. *Scientific Journals of the Maritime University of Szczecin, Zeszyty Naukowe Politechniki Morskiej w Szczecinie* 77 (149), pp. 38–46, doi: 10.17402/595.
9. ITU-T (2019) Rec. BT.500-14: Methodologies for the subjective assessment of the quality of television images.
10. Mirusmonov, M., Zhang, G., Ali, J., Lee, S.H., Kim, D.W. & Kim, J. (2023) Effects of users' motivation on their usage of mobile cloud computing. *International Journal of Human–Computer Interaction*, pp. 1–18, doi: 10.1080/10447318.2023.2247612.
11. Netflix (2024) http://download.opencontent.netflix.com/?prefix=AV1/Chimera/Old/ [Accessed: May 07, 2024].
12. Nowicki, K. & Uhl, T. (2017) QoS/QoE in the heterogeneous Internet of things (IoT). In: Batalla, J., Mastorakis, G., Mavromoustakis, C., Pallis, E. (eds) *Beyond the Internet of Things*. Springer, Cham, pp. 165–196, doi: 10.1007/978-3-319-50758-3_7.
13. Ruiz, D., Sladojevic, S., Culibrk, D. & Fernández-Escribano, G. (2013) Comparison of compression performance of 10-bit vs. 8-bit depth, under H.264 Hi422 profile. *11th International Conference on Telecommunication in Modern Satellite, Cable and Broadcasting Services* (*TELSIKS*), pp. 119–122, doi: 10.1109/TELSKS.2013.6704904.
14. Tariq, J., Javed, M., Rahman, H., Armghan, A. & Ijaz, A. (2024) AI application in video: Spiral optimizer based fast intra mode selection in HEVC. *Multimedia Tools and Applications* 83, pp. 66463–66478, doi: 10.1007/s11042-024-18268-y.
15. Topiwala, P., Krishnan, M. & Dai, W. (2018) Performance comparison of VVC, AV1, and HEVC on 8-bit and 10-bit content. *Applications of Digital Image Processing XLI*, vol. 10752, pp. 305–314. SPIE.
16. Ying Jie, H., Kee, N.S. & Omar, B. (2023) Factors influencing the willingness to pay on tencent video platform: A study among online users in China. *Remittances Review* 8 (4), pp. 3302–3313, doi: 10.33182/rr.v8i4.227.
17. Zeng, Q., Zhuang, Y., Hai, J., Pan, Q., Yin, Z., Chen, Q. & Liang, J. (2023) Challenges of livecast computing network: A contemporary survey. *2023 International Conference on Networking and Network Applications* (*NaNA*), pp. 690–697, doi: 10.1109/NaNA60121.2023.00119.
18. Zmysłowski, D., Kelner, J. M. & Falkowski-Gilski, P. (2023) Mobile networks' analysis in terms of QoS performance assessment. *19th EAI International Conference* (*MobiQuitous*).

Cite as: Falkowski-Gilski, P., Uhl, T., Divakarachari, P.B. (2024) Subjective quality evaluation of 8- and 10-bit MP4-coded video sequences from Netflix. S*cientific Journals of the Maritime University of Szczecin, Zeszyty Naukowe Politechniki Morskiej w Szczecinie* 79 (151), 30–38.

© 2024 Author(s). This is open accesss article licesed under the Creative Commons Attribution (CC BY) License (https://creativecommons.org/licenses/by/4.0/).