Towards Quality of Experience Determination for Video in Augmented Reality Settings

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Abstract

With the continuous growth in the consumer markets of mobile smartphones and increasingly in augmented reality wearable devices, several avenues of research investigate the relationships between the quality perceived by mobile users and the delivery mechanisms at play to support a high quality of experience for mobile users. In this paper, we present the first study that evaluates the relationships of mobile movie quality and the viewer-perceived quality thereof in an augmented reality setting with see-through devices. We find that participants tend to overestimate the video quality and exhibit a significant variation of accuracy that leans onto the movie content and its dynamics. Our findings, thus, can broadly impact future media adaptation and delivery mechanisms for this new display format of mobile multimedia.

Keywords: Augmented reality, Multimedia systems, Image quality, Quality of service

1. Introduction

In recent years, the amount of connected devices that are carried by mobile users has increased drastically and will become one of the dominant drivers for future mobile networking, as described by Cisco, Inc. [1]. A secondary forecasted trend is the continuously large fraction of mobile data that is required due to multimedia consumption while users are “on-the-go.” While currently, smartphones and tablet computers are the dominant form of media consumption and display, the prospect of reality-augmenting wearable devices will likely account for a significant portion of the interaction with mobile multimedia content in future immersive communications systems [2]. Augmented reality has been an area of research in ubiquitous computing for some time [3] and is subject to ongoing research efforts [4]. Several application scenarios were evaluated in recent years in different areas, such as smartphone-based information overlay systems [5, 6], outdoor systems with multiple elements [7, 8], navigation [9], or general information systems combining both [10].
Several industry-based solutions were developed recently in parallel to augmented reality devices, which target the multimedia playback application scenario in the predominantly consumer market space. Augmented reality devices that are performing in a heads-up-display (HUD) or Head-Mounted Display (HMD) manner are increasingly targeting the professional and consumer application space alike, indicating future broad adaptation. While augmented reality devices are available in a broad variety of implementations, see, e.g., [11], for an overview of different types, a slow convergence of systems has begun, especially in the consumer space. Examples for these devices include the Oculus Rift, Sony HMZ-T1 Personal 3D Viewer, Epson Moverio BT-100, or Google Glasses. We note that only the latter two are optical see-through devices and thus similar to the one presented in [12], showcasing how these device types have undergone additional improvements and are now consumer-graded.

The evaluation of these types of systems and related issues have attracted different research groups and a recent survey [13] highlights ongoing issues for the various system types. Evaluations performed also target the user-perception of augmentation for daily life scenarios, such as in [14], or how to limit the amount of additional information, as in, e.g., [15]. Perceptual evaluations oftentimes consider the segmentation of virtualized/augmented items, such as in, e.g., [16]. There are several constraints that have to be considered in this particular scenario, especially from a communications point of view, when targeting the delivery of video data to these types of systems, as the replication of video content with natural features might behave significantly different from overlaid computer-generated information. In [17], the authors evaluate an industrial system that consists of an opaque HMD that displays video sequences at different target bitrates (and resulting imperfection or distortion levels) and user select different encoder properties at the target rate-points, resulting in a combination of framerate and compression. Our evaluation is significantly different in that we provide participating users with a see-through HMD at prescribed video frame rates. Significant differences can be expected for the perceived video quality based on the type of the visual display [13]. In this paper, we investigate the applicability of existing video quality metrics, such as the frequently used PSNR, in the augmented reality space and correlate encoded video quality with subjectively rated perceived video quality levels. The perceptual video quality is measured using mean opinion scores (MOS) obtained from multiple human test subjects according to [18]. The broad potential for implementation in future systems that contain augmented reality display modalities is manifold, as content adaptations for specific video material might benefit content and network providers while maintaining a sufficiently high level of quality of experience [19].

In the remainder of this paper, we initially describe the measurement setup (including the wearable device, the developed mobile application, and the encoded video characteristics) in greater detail. We continue with a detailed description of the obtained results in Section 3 and evaluate the participating users' video quality selection performance in Section 4. We conclude with an outlook on future activities in Section 5.

2. Measurement Setup

In this section, we initially describe the employed wearable head-mounted optical see-through display and the application we developed for the experimentation. We con-
2.1. Augmented Reality Heads-Up Display

We employed the Epson Moverio BT-100 mobile viewer, which consists of a wearable 3D glasses heads-up display unit and a central processing unit. The processing unit features both a directional pad and a touch pad and employs the Android Operating System version 2.2 ("Froyo"). The unit is connected via wires to deliver video signals and power to the see-through display unit, with a display control being integrated into the wired connection. We illustrate the overall system units in Figure 1.

The display unit has a resolution of 960 x 540 pixels of 24-bit color with LED light sources and a 23 degree field of view. Without the additionally available shade, a maximum of 70 % transparency is realized for the display. The images are projected from a display panel built into the device’s sides, from which light is reflected through a lens, and in turn hits a half-mirror layer in the light guide material. This approach results in a portable and readily extensible augmented reality capable head-mounted optical see-through display.

2.2. Mobile Application

We developed a mobile Android application that can be executed on the wearable display’s control unit. The application displays a movie sequence (video and audio content), followed by a Likert-scale question to rate the quality of the last displayed sequence. We illustrate this approach in Figure 2.

Initially, a random quality for a movie sequence is selected and its value stored in a text file on-device before starting the audio/video play-out from on-device storage. After play-out, the user is asked to select a quality level from a presented Likert-scale, with each selection of a quality level captured in the same text file on-device. This process continues until all movie sequences are played out. The created text file with the randomly chosen movie qualities and user rankings of movie qualities can afterwards be copied from the device to a desktop computer for further processing.
2.3. Multimedia Description

We employ the publicly available and Creative Commons licensed *Tears of Steel* short movie as source, which depicts an epic struggle between humans and robots in the future. The video was made by the Blender foundation, merging computer–generated graphics generated by the open–sourced Blender software with real–world filmed scenes in Amsterdam, The Netherlands. We employ this short film as representative of today’s video contents which commonly feature a combination of real–world and computer–generated source materials (we refer the interested reader to [http://tearsofsteel.org](http://tearsofsteel.org) for more details about the movie).

We employ the publicly available 720p version of the movie and segment this source into logically connected scenes for processing, as illustrated in Figure 3. The individual video segments were resized to support the native resolution of the augmented reality glasses and re–encoded using the popular open–source ffmpeg video tool. The encoder used was libx264 with constant rate factor settings of 1, 30, 35, 40, and 45, resulting in a constant quality encoding with variable bitrates. The output was visually inspected to ensure that the settings provided significant differences in visual quality to allow mapping to a quality scale from 1–5, respectively. This represents quality level differences observable within typical streaming scenarios; the resulting values for the PSNR as an objective video quality metric comparing the source video quality to the encoded video are provided in Table 1.

The average segment length is 1486 frames, with the shortest segment covering 817 frames and the longest segment covering 3499 frames. Segments 4 and 10 contain significantly less frames than the other segments; this was required to group multiple scenes into logically fitting segment enabling end of segment questioning about quality. The longest segment of the movie is the last one, which includes the titles and a short end sequence. The average quality in each segment $s$, denoted as $q_s$ and measured as averaged PSNR of the video frames within the sequence, is above 55 dB for the highest quality level and just above 29 dB for the lowest. The largest difference typically is encountered from the highest quality level to the second one, representing the introduction of visually
Table 1: Overview of characteristics for the *Teas of Steel* movie used for experimentation segmented into shorter segments at different quality levels. The typical difference between quality levels is 3 dB, starting with visually identifiable losses in the second quality level.

| Segment | Frames | Level | $q^\text{min}$ [dB] | $r_0$ [dB] | $q^\text{max}$ [dB] | $\sigma(q_s)$ [dB] | CoV$(q_s)$ |
|---------|--------|-------|----------------------|------------|----------------------|-------------------|----------|
| 1       | 1548   | 1     | 52.497               | 64.350     | 188.131              | 27.402            | 0.426    |
|         |        | 2     | 54.854               | 65.035     | 188.131              | 25.165            | 0.350    |
|         |        | 3     | 52.056               | 62.205     | 188.131              | 25.619            | 0.607    |
|         |        | 4     | 29.391               | 39.375     | 188.131              | 26.101            | 0.663    |
|         |        | 5     | 26.715               | 36.380     | 188.131              | 26.305            | 0.726    |
| 2       | 1327   | 1     | 53.190               | 58.963     | 188.131              | 5.713             | 0.097    |
|         |        | 2     | 35.835               | 41.321     | 188.131              | 5.174             | 0.125    |
|         |        | 4     | 29.391               | 38.332     | 188.131              | 5.205             | 0.133    |
|         |        | 5     | 26.715               | 36.380     | 188.131              | 5.226             | 0.147    |
| 3       | 1209   | 1     | 33.333               | 57.216     | 65.594               | 2.753             | 0.048    |
|         |        | 2     | 36.339               | 40.791     | 44.755               | 1.444             | 0.036    |
|         |        | 4     | 30.428               | 34.572     | 38.952               | 1.612             | 0.047    |
|         |        | 5     | 27.736               | 31.334     | 35.909               | 1.627             | 0.052    |
| 4       | 823    | 1     | 52.859               | 36.331     | 65.128               | 2.926             | 0.052    |
|         |        | 2     | 34.397               | 39.332     | 43.729               | 1.742             | 0.044    |
|         |        | 4     | 30.292               | 35.573     | 38.176               | 1.895             | 0.057    |
|         |        | 5     | 27.247               | 32.500     | 62.358               | 3.096             | 0.095    |
| 5       | 1227   | 1     | 53.333               | 57.216     | 65.594               | 2.753             | 0.048    |
|         |        | 2     | 36.339               | 40.791     | 44.755               | 1.444             | 0.036    |
|         |        | 4     | 30.428               | 34.572     | 38.952               | 1.612             | 0.047    |
|         |        | 5     | 27.736               | 31.334     | 35.909               | 1.627             | 0.052    |
| 6       | 1699   | 1     | 52.084               | 56.691     | 65.310               | 2.856             | 0.051    |
|         |        | 2     | 33.964               | 37.876     | 44.670               | 1.465             | 0.039    |
|         |        | 4     | 29.936               | 31.946     | 39.660               | 1.560             | 0.044    |
|         |        | 5     | 26.379               | 29.164     | 34.903               | 1.809             | 0.059    |
| 7       | 1308   | 1     | 51.812               | 55.879     | 65.490               | 2.743             | 0.049    |
|         |        | 2     | 33.964               | 37.876     | 44.670               | 1.465             | 0.039    |
|         |        | 4     | 29.936               | 31.946     | 39.660               | 1.560             | 0.044    |
|         |        | 5     | 26.379               | 29.164     | 34.903               | 1.809             | 0.059    |
| 8       | 1160   | 1     | 52.162               | 56.682     | 65.310               | 2.812             | 0.050    |
|         |        | 2     | 33.748               | 40.078     | 43.437               | 1.493             | 0.037    |
|         |        | 4     | 27.779               | 34.425     | 37.905               | 1.675             | 0.043    |
|         |        | 5     | 25.204               | 31.334     | 34.926               | 1.615             | 0.052    |
| 9       | 1737   | 1     | 52.162               | 56.682     | 65.310               | 2.812             | 0.050    |
|         |        | 2     | 33.748               | 40.078     | 43.437               | 1.493             | 0.037    |
|         |        | 4     | 27.779               | 34.425     | 37.905               | 1.675             | 0.043    |
|         |        | 5     | 25.204               | 31.334     | 34.926               | 1.615             | 0.052    |
| 10      | 817    | 1     | 51.594               | 56.337     | 65.958               | 3.067             | 0.054    |
|         |        | 2     | 43.013               | 38.588     | 43.726               | 2.076             | 0.054    |
|         |        | 4     | 28.087               | 32.501     | 37.993               | 2.502             | 0.073    |
|         |        | 5     | 25.524               | 29.916     | 35.196               | 2.924             | 0.081    |
| 11      | 1216   | 1     | 52.913               | 57.495     | 188.131              | 1.688             | 0.038    |
|         |        | 2     | 35.194               | 39.333     | 188.131              | 17.064            | 0.429    |
|         |        | 4     | 32.010               | 36.529     | 188.131              | 13.249            | 0.363    |
|         |        | 5     | 29.968               | 33.671     | 188.131              | 13.503            | 0.301    |
| 12      | 3499   | 1     | 49.845               | 61.468     | 188.131              | 25.622            | 0.417    |
|         |        | 2     | 30.756               | 41.336     | 188.131              | 29.331            | 0.710    |
|         |        | 3     | 26.761               | 38.066     | 188.131              | 30.013            | 0.888    |
|         |        | 4     | 23.177               | 35.326     | 188.131              | 30.013            | 0.888    |
|         |        | 5     | 19.926               | 32.158     | 188.131              | 31.223            | 0.981    |
recognizable encoding losses. Afterwards, the difference between the different quality levels is around 3 dB. Comparing the variability of the individual video frame $i$ quality $q_{i,s}$ in the different segments, either as standard deviation $\sigma(q_s)$ or coefficient of variation $\text{CoV}(q_s)$, we observe a significantly higher level for the first and last two segments of the video. The reason for this increased level is the number of all–black and title/credit content video frames that are encountered in the beginning of the movie and towards the end. The homogeneous single–color content increases the coding efficiency and results in no measurable coding losses, bringing the PSNR to an increased level (indicated by the maximum video frame quality value $q_{s,\text{max}}$).

We additionally note that we do not process the audio component of the movie segments and copy the original audio source to the various new segment versions.

2.4. Experimental Set-Up

Original research protocol submission to the Institutional Review Board (IRB) at Central Michigan University was performed in February, 2014 and approval was obtained beginning of April, 2014. Participating volunteers were recruited from students, faculty, and staff of the Department of Computer Science at Central Michigan University from April through May, 2014. The participants were instructed about the nature of the experiment and its overall procedural flow; this was followed by a description of the wearable display and the required interaction with it. The instruction part was followed by consent form administration before fitting the wearable display and commencing experimentation. The experiments took place in well–lit office spaces and classrooms, with participants being instructed to look at a stretch of white wall or a whiteboard to allow for comparability of results. All of the participants used the in–ear headphones to play back audio accompanying the visual content to be evaluated.

3. Experimental Results

In this section, we discuss the results obtained through the experimentation with participants. We report findings for experiments conducted with 15 volunteers, which is the required sample size for audio–visual experiments outlined in [18].

3.1. Overall Results

We initially present the encoded video quality levels $v$ and the participant–selected qualities $p$ for each user $u$ and segment $s$ in Table[2]. The overall average for the randomly chosen video quality levels is $\mu_v = 2.94$ with a standard deviation of $\sigma_v = 1.44$, while the user–selected ones exhibit a higher average with slightly smaller variability ($\mu_p = 3.13, \sigma_p = 1.24$). The differences between the two indicates that users overall select slightly higher quality levels than actually encoded. Comparing the means through an ANalysis Of VAriance (ANOVA) to test for difference of means reveals that they are to be considered related $F(1, 354) = 1.89, p > 0.169$. For all pairs, independently of the segment, we observe a correlation of $\rho_{v,p} = 0.62$, which indicates a possible relationship between the encoded video quality level and user–identified one.
Table 2: Experimental results for encoded video quality levels $v$ and the participant–selected qualities $p$ for each user $u$ and segment $s$.

| Segm. $s$ | Mode $v/p$ | User $u$ |
|----------|------------|----------|
| 1        | $v$        | 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 |
|          | $p$        | 1 3 5 1 3 5 1 3 5 1 3 5 1 3 5 |
| 2        | $v$        | 4 4 4 5 4 2 2 3 2 3 4 1 4 4 3 |
|          | $p$        | 5 3 1 5 2 3 2 4 3 4 1 2 1 5 4 |
| 3        | $v$        | 4 2 1 5 1 5 3 3 3 3 1 2 1 4 3 |
|          | $p$        | 5 3 1 5 2 3 2 4 3 4 1 2 1 5 4 |
| 4        | $v$        | 3 1 4 1 5 4 3 4 5 3 3 5 1 5 5 |
|          | $p$        | 5 2 4 5 3 3 4 4 4 2 3 1 5 5 |
| 5        | $v$        | 5 1 1 2 1 1 2 3 4 3 4 3 3 3 3 |
|          | $p$        | 5 3 2 3 1 2 1 3 3 4 2 3 2 3 4 |
| 6        | $v$        | 3 5 2 2 2 3 4 3 4 4 1 3 3 3 5 |
|          | $p$        | 5 3 3 3 3 2 2 4 4 4 2 3 1 5 4 |
| 7        | $v$        | 1 2 5 1 1 2 2 3 1 5 4 2 1 5 4 |
|          | $p$        | 2 3 4 3 2 2 2 3 1 4 3 2 3 1 5 4 |
| 8        | $v$        | 3 5 4 2 2 1 1 2 3 1 4 2 1 2 2 |
|          | $p$        | 5 4 3 3 3 1 1 2 3 2 3 2 1 5 3 |
| 9        | $v$        | 3 3 3 1 3 4 4 1 1 5 1 4 2 2 2 |
|          | $p$        | 5 3 3 1 3 4 4 1 1 5 3 4 1 5 3 |
| 10       | $v$        | 4 1 3 1 3 2 5 1 1 5 5 5 5 5 3 |
|          | $p$        | 5 3 3 1 2 3 4 1 2 4 3 3 4 5 4 |
| 11       | $v$        | 1 3 4 4 4 5 4 4 5 4 4 2 5 2 1 |
|          | $p$        | 2 3 5 5 3 4 4 4 5 4 3 2 4 5 3 |
| 12       | $v$        | 3 2 4 2 4 3 1 1 4 3 4 1 3 2 4 |
|          | $p$        | 3 3 4 4 3 3 2 3 3 1 1 2 4 3 5 |
Table 3: Overview of correlation and paired sample T–Test two–tailed significance values for segment–based video quality levels and user selections.

| Segm. s | Samples N | Diff. Av. $\mu_{v-p}(s)$ | Diff. Std. Dev. $\sigma_{v-p}(s)$ | Corr. $\rho_{v,p}(s)$ | T | Sign. p |
|---------|-----------|--------------------------|-------------------------------|------------------|----|--------|
| 1       | 15        | -0.067                   | 1.486                         | 0.562            | -0.174 | 0.865 |
| 2       | 15        | -0.2                     | 1.568                         | 0.446            | -0.494 | 0.629 |
| 3       | 15        | -0.267                   | 0.884                         | 0.809            | -1.169 | 0.262 |
| 4       | 15        | -0.267                   | 1.163                         | 0.563            | -0.888 | 0.389 |
| 5       | 14        | 0.071                    | 0.997                         | 0.725            | 0.268  | 0.793 |
| 6       | 15        | -0.067                   | 1.387                         | 0.255            | -0.186 | 0.855 |
| 7       | 15        | -0.267                   | 0.961                         | 0.706            | -1.076 | 0.301 |
| 8       | 15        | -0.4                     | 1.121                         | 0.603            | -1.382 | 0.189 |
| 9       | 15        | -0.467                   | 1.06                          | 0.718            | -1.705 | 0.11  |
| 10      | 15        | 0.133                    | 1.187                         | 0.720            | 0.435  | 0.67  |
| 11      | 15        | -0.267                   | 1.163                         | 0.554            | -0.888 | 0.389 |
| 12      | 14        | -0.286                   | 1.383                         | 0.368            | -0.773 | 0.453 |

3.2. Individual Segments

Next, we consider the relationship within the individual segments to derive a more detailed view on the participant selection given content and segment length differences. We compare the pair–wise correlation between the set and user–selected video quality values on the 5–point scale and their two–tailed T–Test significance (for a 95 % confidence level) in Table 3. We initially observe that with exceptions for segments 5 and 10, the difference average is slightly negative, indicating that on average, participants chose higher quality levels than displayed. The comparatively large standard deviation indicates that users deviate significantly from the actual displayed values in almost every segment, with the exceptions of segments 8 and 9. These two segments exhibit higher levels of content dynamics as the plot of the movie moves towards its climax. We note that the correlation is with few exceptions over 0.5, indicating again that user–selected values and randomly displayed video quality levels are potentially related. We compare these findings by performing paired T–Tests for the individual user selections in each segment and present results in Table 3 as well. The relatively small differences in average, paired with the calculated standard deviations, do not indicate that there is a statistically significant difference between the video categories presented and the ones that were participant–selected, which is corroborated by the $p$–values obtained for the individual segments. The smallest $p$–value determined is 0.11, which is slightly above typical significance levels.

3.3. User Selected Differences

As an additional evaluation, we consider the difference between the video quality level and the user–selected level individually. We illustrate the segment–dependent stacked spread in Figure 4. We initially notice that all segments exhibit a spread between users choosing either higher or lower levels than actually observed. Observing the differences closer, we note that users tend to over–estimate the quality in segments 3, 7, 8, and 9 to a higher degree than in the other segments. The differences can be partially explained
by the higher excitement levels that are present in these segments’ scenes and accompanying audio. This observation additionally indicates that the higher correlation levels we observed earlier for these sequences stem from the general over-evaluation of the video quality by a significant number the participants.

4. Selection Performance

In this section, we interpret the selection of the video quality by participants as a retrieval process and calculate the typical performance measures. We denote the user-selected quality level $u$ and the randomly displayed encoded video quality level $v$ for each segment $s$ as in the preceding Section 3.

4.1. Metrics

We employ the common notation introduced in, e.g., [20], by defining the confusion matrix in dependence of a specific video quality level $\nu$ (where $[\cdot]$ denotes the Iverson Bracket) as follows:

\begin{align*}
\text{TruePositive} & \quad tp(\nu) = \sum_{s,u} [v(s,u) = \nu] \cdot [u(s,u) = \nu] \\
\text{FalsePositive} & \quad fp(\nu) = \sum_{s,u} [v(s,u) \neq \nu] \cdot [u(s,u) = \nu] \\
\text{FalseNegative} & \quad fn(\nu) = \sum_{s,u} [v(s,u) = \nu] \cdot [u(s,u) \neq \nu] \\
\text{TrueNegative} & \quad tn(\nu) = \sum_{s,u} [v(s,u) \neq \nu] \cdot [u(s,u) \neq \nu]
\end{align*}
Figure 5: Selection performance results in terms of accuracy and $F_1$-score depending on the video quality level $v$. Medium video quality level ranges result in lower participant selection performance.

Omitting the relationship to $\nu$ for clarity, the common performance metrics are defined as:

\begin{align*}
\text{Accuracy} & \quad acc = \frac{tp + tn}{tp + fp + fn + tn} \\
\text{Precision} & \quad prec = \frac{tp}{tp + fp} \\
\text{Recall} & \quad rec = \frac{tp}{tp + fn} \\
\text{F - Score} & \quad F_1 = \frac{2 \cdot prec \cdot rec}{prec + rec}
\end{align*}

We employ these values to determine the performance of the participant selection of a displayed video quality as result of the human quality perception in relationship to the encoded video quality levels for the individual segments.

4.2. Video Quality Dependence

We initially note an overall average accuracy in video quality selection of $acc = 75.6\%$ (or error rate of 25.4\%), indicating that for the majority of segments, participants were able to discern the video quality without training correctly into one of the five quality levels. The precision and recall values observed are $prec = 40.8\%$ and $rec = 35.9\%$, respectively, resulting in an $F_1$-score of $F_1 = 0.38$. This indicates that overall, users were only exhibiting low–medium ability to correctly identify the video quality level. The error rate can be explained by the nature of the see–through display, which might allow certain types of video quality impairments to go unnoticed. The dependency of the different values becomes more apparent when evaluating the user performance in dependency of the underlying video quality, as illustrated in Figure 5.

We observe that the accuracy and $F_1$ scores both start on a high level, decrease with higher quality levels, followed by an additional increase. Only the $F_1$ score exhibits a slight decrease for the highest quality. The accuracy is the lowest for the medium quality, which can be explained with parts of sequences exhibiting higher levels of complexity, which result in higher levels of compression artifacts even in medium quality settings. As
Figure 6: Segment–dependent participant selection performance. Selection performance coincides with overall movie content and storyline dynamics.

a result, participants are rating the displayed quality lower than it actually is; opposite considerations apply for a better quality rating. At the extreme ends, there are either significant quality impairments throughout a segment or only very few, which likely makes it relatively easy to discern these endpoints and, thus, results in higher accuracy.

4.3. Segment Dependence

We now shift the view to evaluate the impact of the content present in the different segments on the accuracy and $F_1$ score of the participants’ selection of the video quality when compared to the actual ones, illustrated in Figure 6.

We observe an average accuracy that overall remains around or above 70 %. We note an initial rise, followed by a drop to the middle of the complete movie, followed by an increase and a final decrease. This behavior is followed closely by the $F_1$ score as well, but with larger differences in the rising and falling trends. Segment 9 exhibits the highest values for both, with an accuracy above 85 % and an $F_1$ score just above 60 %. As a segment with several highly dynamic action–scenes, the imperfections become more obvious, e.g., pixelations or blockiness in explosions. However, the rise to this point also coincides with the tension of the actual movie (that climaxes in segments 9 and 10), which might be an additionally contributing factor. Overall, these results indicate that content variation has an impact on accuracy and precision/recall and needs to be considered as in regular display facilities for video encodings.

5. Conclusion

The mobile consumption of movie content in augmented reality settings gives rise to the question of how mobile users perceive the display of multimedia content on their devices; here, we presented the the first study addressing this research domain for wearable see–through displays.

For the publicly available Tears of Steel short movie, segmented into multiple shorter sequences, we find that users tend to slightly overestimate the video quality, with no statistically significant difference of means (but approaching it for individual segments).
The participant–selected high quality levels tend to correlate with the content of the segments, with higher levels of content dynamics exhibiting larger positive ratings compared to the presented video quality level. Though overall, we notice a medium–high accuracy level around 75 %, the precision and recall values are significantly lower, corroborating the general results. We reason that a significant portion of the positive viewer bias stems from the nature of the optical see-through device, which likely obscures smaller visual imperfections when compared to a traditional display method. This is substantiated by participant selections exhibiting higher levels of accuracy, precision, and recall for high and low video quality levels throughout, but lower values in the medium range, where some obfuscation might lead to higher quality ratings.

Future multimedia delivery systems targeting this form of media display can take these findings into account to optimize content modification and delivery mechanisms. Future research avenues can evaluate more interplays of audio quality or “background” real–world settings and their influence on the perceived quality.

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