Subjective Assessment of Region of Interest-aware Adaptive Multimedia Streaming Quality

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***Abstract*—Adaptive multimedia streaming relies on adjusting the video content's bit-rate in order to meet network conditions in the quest to reduce packet loss and resulting video quality degradations. Current multimedia adaptation schemes uniformly adjust the compression over the entire image area. However research has shown that user attention is focused mostly on certain image areas, denoted Areas of Maximum User Interest (AMUI), and their interest decreases with the increase in distance to the AMUI. The Region of Interest-based Adaptive multimedia Streaming scheme (ROIAS) is introduced to perform bit-rate adaptation to network conditions by adjusting video quality relative to the AMUI location. This paper also extends ROIAS to support multiple areas of maximum user interest within the same video frame. The paper presents the performance analysis of ROIAS in terms of the impact on user perceived video quality measured using subjective video quality assessment techniques based on human subjects. The tests use a wide range of video clips which differ in terms of spatial and temporal complexity and region of interest location and variation. A comparative evaluation of both subjective and objective video quality test results is performed and demonstrate the benefit of using ROIAS for adaptive video quality delivery.**

***Index Terms*—Multimedia streaming, content adaptation, user perceived quality, region of interest.**

I. Introduction

Multimedia applications are increasingly popular among Internet users. This class of applications include IP television (IPTV), voice-over-IP (VoIP), video-on-demand and teleconferencing. They are characterized by high sensitivity to network Quality of Service (QoS) parameters such as loss, delay, and delay jitter and they have very high bandwidth requirements [1].

In terms of network support, most network environments are best-effort; at the same time wireless access networks gain popularity. Different technologies and network connectivity solutions exist. These lead to an overall dynamic networking environment with respect to QoS levels [2].

Considering these aspects, maintaining a high level of video content quality and consequently a high level of user satisfaction becomes a challenging task. For short term variability of network conditions a buffering solution can be used successfully at the receiver side [3].

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However the long term dynamics of the network conditions cannot be overcome by using this technique. Among the solutions to this problem, which include scalable video encoding [4] and multiple description coding [5], adaptive multimedia streaming is one of the most efficient [6], [7], [8]. Adaptive multimedia streaming aims at improving the user perceived video quality by adapting the multimedia stream's bit-rate to match the current capacity of the transport network [9], [10], [11].

Various multimedia content bit-rate adaptation schemes have been previously proposed in the literature [9]. These adaptive streaming techniques follow the architecture presented in Fig.1 and rely on the variation of some QoS parameters in their decision making process. However these network level QoS parameters are poorly related to the quality of the video content as it is perceived by the human visual system [12]. Under these circumstances more advanced adaptation schemes have been proposed in the literature, such as the Quality Oriented Adaptive Scheme (QOAS) [13] which considers estimations of user perceived quality during the adaptation process. The solution proposed in [14] also targets an improved video quality but the content adaptation is performed by adjusting the resolution.

A common characteristic of most adaptive multimedia streaming schemes is the fact that the image area is treated uniformly during the adaptation process. However research has shown [15] that user attention is mostly focused on a specific area in each particular frame or group of frames, denoted Area of Maximum User Interest (AMUI), while viewer interest decreases with the increase in distance to this AMUI. Considering this fact, the Region of Interest-based Adaptive multimedia Streaming scheme (ROIAS) [16] adjusts the compression rate distinctly for each image area within a frame according to the user interest in it.

Although ROIAS has been previously tested using objective quality metrics [16], actual validation with potential users has not yet been attempted. This is especially important given the debate in the literature regarding the limitation of the correlation between existing objective quality metrics and subjective/perceptual video quality assessment.

Moreover, the issue of how to degrade the (higher) video quality contained in an area of maximum user interest, to the lower quality associated with the background of the screen real estate has, to the best of our knowledge, not been previously addressed. This again is an issue which needs to be examined, even more so given the perceptual annoying boundary effects which can occur between areas of high and, respectively, low video quality [15].

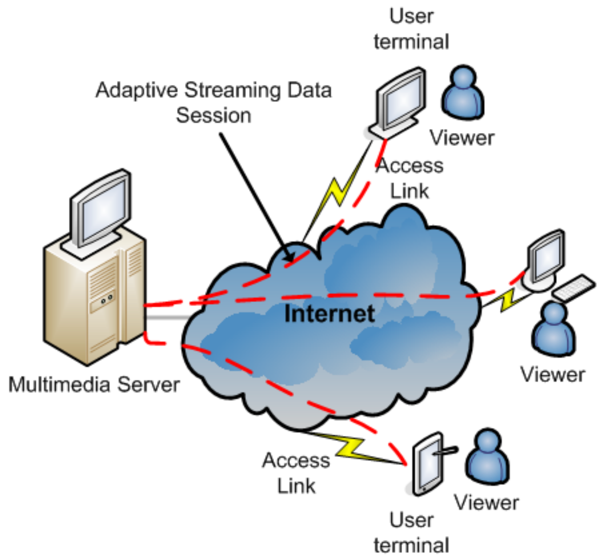

Fig. 1. Adaptive Multimedia Streaming.

Consequently this paper makes three contributions to the existing state of the art. It presents ROIAS as a very good user perceived quality-oriented adaptive multimedia delivery solution, it extends ROIAS to support multiple areas of user interest and the paper performs ROIAS performance validation in terms of user perceived quality. This validation includes a subjective assessment-based study of ROIAS effects on user perceived quality and a comparison-based analysis of subjective and objective quality assessment results.

The structure of the paper is as follows: section II presents several existing multimedia adaptation schemes along with results of research conducted in the area of region of interest encoding techniques. Video quality assessment metrics and techniques are also discussed in this section. ROIAS is presented in section III which details its architecture and presents a mathematical model based on which the compression rate is adapted. Section IV details the methodology for video quality assessment used to evaluate the performance of ROIAS with respect to user quality of perception. Section V presents a statistical analysis of the results and compares the results obtained by objective metrics with those of subjective perceptual testing. Finally, conclusions and possibilities for further work are described.

II. Related Works

A. Adaptive Multimedia Streaming

User satisfaction is crucial for the success of any multimedia-based application. Various performance issues arise when multimedia content is delivered over best-effort networks to users with heterogeneous device capabilities and expectations. However network conditions in terms of available bandwidth, packet loss and packet delay and delay jitter have a major impact on the quality of delivered multimedia content and its timeliness, ultimately affecting the end-user perceived quality or as it is most recently termed Quality of Experience (QoE).

In order to avoid the negative impact dynamic network conditions have on the multimedia content, measures have to be taken to adapt the streaming process to follow and match the current network capacity. If short term variations can be overcome by using buffering techniques [3], for long time-scale network dynamics rate adaptation techniques are among the most efficient solutions.

Several adaptive streaming solutions were proposed at the network and transport layer including TFRCP [17], LDA+ [18] and RAP [19]. These solutions present a reasonable performance in terms of QoS but their major drawback is a poor correlation with the actual end-user perceived quality.

More advanced adaptive streaming techniques from the point of view of maintaining a high level of user perceived quality were developed at the application layer. Such a solution with good performance in terms of user perceived quality is LQA [20]. Cross layer methods get closer to the user and try to achieve higher perceptual quality of streamed multimedia content. A good survey of these solutions can be found in [21].

The Quality Oriented Adaptation Scheme (QOAS) [22] involves a user perceived quality estimation in the feedback-based multimedia adaptation process. Consequently QOAS shows significant improvements in end-user perceived quality when used for streaming multimedia content in both wired and wireless networking environments.

Diverse solutions were proposed for adaptive multimedia transmissions over wireless access networks [23] or wireless ad-hoc networks [24]. Among the proposed solutions are adaptation mechanisms at the level of layers [23] or objects [25], fine-granular scalability schemes [26] and perception-based approaches [27].

However all these solutions involve content adjustments which affect equally the whole area of the video frames, regardless of different user interest in various frame regions as research on regions of interest (ROI) has demonstrated [15].

A cross layer adaptive multimedia streaming solution was proposed in [28]. Unlike the other solutions discussed above, this one makes distinction between various elements of the video content by identifying, classifying and assigning different priorities and consequently different QoS levels for each element or group of elements. However this solution does not consider the variation in user attention focus during the video sequence.

A ROI-based adaptive scheme is introduced in [29]. Unlike in the case of ROIAS, each macro-block is categorized as ROI or non-ROI based on a saliency map computed using luminance contrast, color-double-opponent, texture, skin color and motion vector.

ROI-based adaptation of video content is also discussed in [30]. Although techniques for estimating the ROI within a video frame are presented the adaptation consists in adjusting the frame resolution to match the maximum display resolution.

A similar approach is presented in [31]. Unlike ROIAS the proposed solution focuses on resolution adaptation and targets specific types of content (i.e. news, interviews) where the ROI is predefined at the beginning of the material and then is tracked throughout the playback.

The solution presented in [32] estimates the RoI on the server side and drops all pixels which are not within the RoI. The client reconstructs the lost pixels using liner interpolation based reference frames.

In [33], a user controlled RoI-based streaming solution is presented. The user decides which slice of a higher resolution stream he/she wants to see and the server will preferentially deliver the requested RoI.

Although ROI is considered in the adaptation process, the above mentioned solutions do not reach the level of generality and performance in terms of smoothness and adaptability.

B. Region of Interest

Region of Interest research has received considerable attention, especially based on the premise that where a user's gaze rests corresponds to the location of the symbol currently being processed in working memory. Based on this the idea is to allocate more screen resources to the portion on the video image corresponding to the Region of Interest.

Research performed by [34] found that when a high-resolution window was adapted at the point-of-gaze and the resolution in peripheral areas was degraded, the participants' initial saccadic latencies in peripheral areas (the time taken to identify a visual target) increased compared with the case when a low resolution was uniformly displayed across the whole display window.

Loschky and McConkie found that in order to maintain user levels of interest, the size of the adapted high-resolution window at the point of gaze needs to be increased if the degradation level is increased in peripheral areas [35].

In related work, [36] presents a method of automatically determining the perceptual importance of different regions of an image. Based around the human visual system, using grey scale images, Osberger and Maeder merged five factors that were known to influence attention: contrast with region background; region size, shape and location; determination of foreground and background areas. These factors were combined into an overall "Importance map" (IM), which was used to classify the importance of image regions. Based on the IMs, the authors demonstrated a technique for controlling adaptive quantisation processes in an MPEG encoder [37].

More recently, Agrafiotis et al. [38] presented a framework for model-based, context-dependent video coding, which rely on exploiting the human visual system's characteristics. The system utilizes variable-quality coding, based on priority maps which are created using mostly context-dependent rules.

Loschky and Wolverton tackle the interesting issue of perceptual disruptions in Gaze-Contingent Displays (GCDs), specifically examining perceptually acceptable update delays in multi-resolutional displays, showing that an update of 60 ms is ample enough to be perceptually acceptable [39].

C. User Satisfaction and Video Quality Assessment

Video quality assessment methods and metrics are very important for testing adaptive multimedia applications in general and especially for their quality-related evaluation. They are particularly useful to assessment of the effects variable network conditions have on user perceived quality.

Video quality assessment methods can be classified in two categories from the point of view of user involvement in the assessment process: subjective methods and objective metrics [13].

Subjective testing is performed using human observers involved in video perceptual quality assessment [40] and follows methodologies and recommendations such as those from ITU-R BT.500 [41], ITU-T R. P.910 (one way video test methods) [42], and ITU-T R. P.911 (quality assessment methods for multimedia applications) [43].

Objective methods are classified in [44] from the point of view of usability in conjunction with adaptive streaming solutions as out-of service methods (the original sequence is available and no time constraints are imposed) and in-service methods (performed during streaming without original sequence and with strict time constraints).

In relation to the existence of the original multimedia stream during the quality assessment [45] objective methods can be classified into full reference methods (use comparisons with the reference stream), reduced reference solutions (employ feature extraction) and no reference methods [46] (no original stream is required for quality assessment).

Among the most important and widely used objective video quality metrics are the full-reference Peak Signal-to-Noise Ratio (PSNR) [47], Video Quality Measurement (VQM) [48], Structural Similarity (SSIM) [49] and Moving Pictures Quality Metric (MPQM) [50].

PSNR is easy to use, has low computational complexity, but was criticized for poor correlation with human perceived quality [12]. SSIM index is a full reference metric designed to assess the similarities between two images. SSIM aims at being more consistent with the perception of the human eye. VQM measures the perceptual effects of different kind of video impairments such as blurring, jerky motion, blockiness, etc. and provides a higher correlation with subjective quality assessment. Lastly MPQM is an objective metric especially designed to consider some human visual system characteristics such as contrast sensitivity and visual masking. It also has a no-reference version defined for MPEG video streams [51].

A more recent classification [52] of objective video quality assessment metrics shows that VQM and SSIM are among the best performers for the LIVE Video Quality Database [53].

III. Region of Interest-Based Adaptive Streaming

Most existing adaptive streaming solutions treat the video frame area as a whole, without considering individual elements of the content and especially their relevance to user interest. Consequently during the adaptation process the compression factor is adjusted uniformly over the entire video frame area.

Considering the fact that user attention is focused only on a certain area in each particular frame, as previous research has shown [15], and that user interest for a specific frame area decreases with the increase in the distance to the region of highest user interest, all these adaptation schemes do not perform an optimum adjustment of content bit-rate according to the end-user perception particularities.

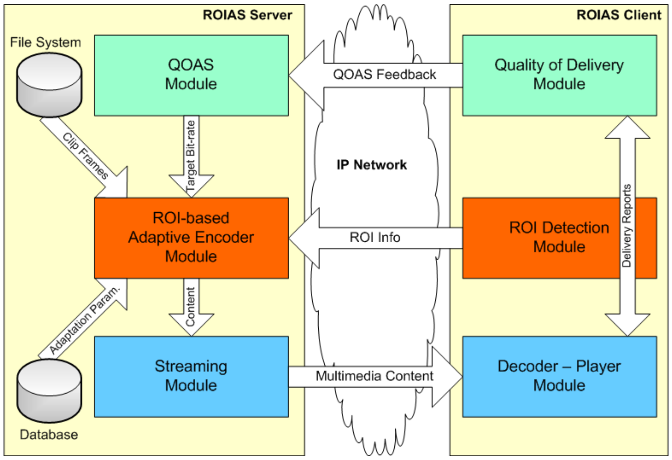

Fig. 2. Region of Interest Adaptive Scheme Architecture

Under these circumstances, the Region of Interest Adaptive multimedia Streaming scheme (ROIAS) performs a differentiated content adjustment process, on a frame by frame basis, based on user interest on certain regions within the frame.

A. System Architecture

Fig. 2 presents the architecture of ROIAS. The systems involves a ROIAS Server module and a ROIAS Client module. The two modules communicate over an IP network, streaming high quality multimedia content and exchanging control information.

Each module (client & server) consist of three sub-modules. QOAS Module and Quality of Delivery Module are in charge of determining the quality of delivery and deciding the target streaming bit-rate. ROI-based Adaptive Encoder and ROI Detection are in charge of establishing the ROI and encoding the content accordingly. The Streaming module and Decoder-Player module are in charge of delivering and displaying the content.

As can be seen in Fig. 2 ROIAS relies on and extends the classic QOAS multimedia adaptation scheme, first introduced in [22]. The QOAS client module, represented in Fig. 2 by the Quality of Delivery Module, monitors and reports to the server side QOAS module on network conditions and multimedia quality of delivery at the client and suggests content bit-rate adjustments to meet the currently available bandwidth.

The QOAS adaptive scheme does not consider end-user region of interest in the adaptation process. QOAS uses a standard video encoder which adjusts the compression level uniformly over the entire frame area to meet the bit-rate requirements requested by the QOAS server side adaptation module.

The ROIAS adaptive scheme extends the classic QOAS system at the encoder level. The ROIAS video encoder adjusts the multimedia content's bit-rate by selectively adjusting the compression factor of some frame regions depending on user interest.

The ROI-based adaptive encoding scheme consists of two main modules. The client side ROI Detection Module estimates the user region of maximum interest by detecting the current viewer's gaze [54]. ROI detection may be achieved by employing intrusive and most importantly non-intrusive equipment using infrared or near-infrared-based light to create a corneal-reflection which is then tracked by a specialised algorithm [1]. Moreover, users can elect whether or not they want to use ROIAS in the rendering of multimedia content.

If the client lacks hardware and/or software support to determine the user interest or has any privacy issues, default values may be used by the server or ROI detection algorithms [55]. These algorithms are well studied in the area of computer vision and considering that these algorithms will be run on the server side (before encoding) their computational requirement can be easily met. However, ROI detection algorithms may not estimate the exact area of maximum interest for a particular user leading to lower video quality from that user's subjective perspective.

The ROI Detection Module is capable to cope with multiple users watching the same video content on the same device. In this circumstance the module will report multiple distinct ROIs which will be treated separately by the server module as presented in Algorithm 1.

The location of the region of maximum user interest is reported to the server side module (i.e. ROI-based Adaptive Encoder Module). Based on the ROI information received from the client module and assuming the principle of locality, both temporal and spatial, the ROIAS server side module defines various Regions of Interest (ROI), concentric around the Area of Maximum User Interest (AMUI). In order to cope with fast changes in user area of interest but within the same scene, ROI-based Adaptive Encoder Module establishes the AMUI between 10% and 20% wider than that reported by the client-side module, depending on the motion complexity of the content. In the case when the video content changes and determines a complete relocation of the AMUI, a scene change detection algorithm [56] is employed and consequently the AMUI area is increased up to the full frame size.

During the adjustment process, ROIAS decreases ROIs multimedia encoding quality gradually as its distance from AMUI increases. In this way, ROIAS achieves higher end-user subjective perceptual quality in comparison to the case when content quality is decreased equally across the whole frame area. The Streaming module at the server side streams the adapted multimedia content over the IP-network to the ROIAS Client.

Although currently unicast multimedia streaming is envisaged only, the ROIAS architecture is so designed as to allow for extension to multicast. ROIAS server-side module will be equipped with a special unit to aggregate users various areas of maximum interest.

B. Mathematical Model

Based on the nature of the dependency between the compression factor chosen for each frame macro bloc and its distance to the area of maximum user interest (i.e. AMUI) two versions of the ROIAS adaptive scheme can be identified: Linear-ROIAS and Logarithmic-ROIAS.

[1] www.smivision.com and www.tobii.com

1) Linear Quality-Distance Adaptation: Equation (1) formalizes the linear dependence between the Quantization Coefficient (QC) and the distance (DIST) of each macro-block from the AMUI. In (1) QCmax is the quantization coefficient associated with the highest video quality in this sequence and AC is the ROI-dependent Adaptation Coefficient, which is varied during adaptive multimedia streaming in order to meet the target bit-rate. The higher AC, the faster QC is rising, leading to a greater reduction in the resulting multimedia stream bit-rate, but also to higher quality degradation.

$$QC(DIST, AC) = QC_{max} + AC * DIST \tag{1}$$

The main advantage of employing linear quality variation for ROIAS is the fact that quality decreases smoothly with the increase in distance from ROI to the AMUI. The main drawback of this degradation technique is the low quality of the macro-blocks positioned furthest from the AMUI, which leads to a poor local user perceived quality.

2) Logarithmic Quality-Distance Adaptation: In a similar fashion with Linear-ROIAS, Logarithmic-ROIAS employs equation (2) to determine the macro-block's Quantization Coefficient (QC)'s value function of the distance (DIST) of the macro-block from the AMUI.

$$QC(DIST, AC) = QC_{max} + AC * log(DIST) \tag{2}$$

The logarithmic dependency is more effective from the point of view of user perceived quality, mainly because the quality degradation starts to be perceived by the user only after a specific threshold is reached. The main advantage of Logarithmic-ROIAS is the fact that it can distribute video quality in a similar manner the human visual system acts, improving overall user perceived quality. Its main disadvantage is that a sharp decrease in quality is performed as the distance to AMUI increases, running into the risk of quality degradation to be observed by the human viewers.

3) ROIAS Adaptation Algorithm: Multiple users watching the same video clip will determine distinct AMUI areas. Under these circumstances in the following section the algorithm for choosing the quantization parameter QC when multiple AMUI exist is detailed. The procedure is presented in Algorithm 1.

Depending on the type of dependency chosen (logarithmic or linear), the position of the AMUI ($\{x, y\}$) and the AC parameter, a different bit-rate BR will be achieved for each frame or group of frames.

Equation (3) indicates how the quantisation factor (QC) value is adjusted based on the position of the pixel and the chosen target bit-rate in order to implement the ROI-based adaptation.

The QC parameter is calculated for each macro block separately as presented in equation (3) where the function QC is the one in equation (1) or (2) and N_{AMUI} is the number of distinct $AMUI_j$ identified. The AC_j parameter is chosen so the target bit-rate T_{BR} (the video content's bit-rate required to meet the network conditions) is achieved for each AMUI independently.

$$QC_j = QC(DIST_j, AC_j), 0 \leq j \leq N_{AMUI} \tag{3}$$

Considering the distance between the macro block to each $AMUI_j$ separately and the corresponding AC_j, a distinct quantization factor QC_j will be calculated. However only one value of QC has to be chosen for encoding the macro block. The expected bit-rate for any particular combination of $AMUI_j$ and AC_j parameter is given by a special estimation function (f) which in this paper was replaced by a database containing all the existing combinations of $AMUI_j$ and AC_j parameter and their corresponding bit-rates preprocessed for each test video sequence separately. The current cumulative bit-rate C_{BR} of the current frame will be calculated after each macro bloc compression process, while the old one L_{BR}, corresponding to the last processed macro block is stored. If the deviation of the current cumulative bit-rate from the target bit-rate is within the boundaries of a preset threshold $BR_{Threshold}$ the minimum value from QC_j will be chosen for QC to achieve maximum quality. If the deviation of the current cumulative bit-rate exceeds the threshold, the maximum coefficient will be chosen if the bit-rate tends to increase or the minimum value, if the bit-rate tends to decrease.

Algorithm 1 Calculate QC for multiple AMUI

Input:
T_{BR};
$BR_{Threshold}$;
$AMUI_i = \{x_i, y_i\}, \vee\ 0 \leq i \leq N_{AMUI}$;
$BR_i = f(AC_i, AMUI_i), \vee AC_{min} \leq AC_i \leq AC_{max}$;
Output:
$QC_j, \vee 0 \leq j \leq N_{MB}$;
Procedure:

```
C_BR ⇐ 0
L_BR ⇐ 0
i ⇐ 0
for all k such that 0 ≤ k ≤ N_AMUI do
    Choose AC_k such as f(AC_k, AMUI_k) = T_BR
end for
while i < N_MB do
    for all j such that 0 ≤ j ≤ N_AMUI do
        QC_j = QC(DIST_j, AC_j)
    end for
    if |T_BR − C_BR| < BR_Threshold then
        QC_i = min(QC_j), ∨0 ≤ j ≤ N_AMUI
    else if C_BR − L_BR > 0 then
        QC_i = max(QC_j), ∨0 ≤ j ≤ N_AMUI
    else
        QC_j = min(QC_j), ∨0 ≤ j ≤ N_AMUI
    end if
    L_BR ⇐ C_BR
    Calculate C_BR
end while
```

IV. Video Quality Assessment

In order to evaluate the performance of the proposed ROIAS-based solutions, client-server multimedia streaming over a "Dumbbell" topology was simulated using the NS-2

Fig. 3. Video sequences used during testing

Network Simulator [57]. The server and clients have been connected via 100 Mbps wired links. QOAS streaming modules have been deployed at the application level using NS-2 UDP agents for data transport. Multimedia clips were streamed to an increasing number of clients using QOAS. For the adaptation, QOAS used five target bit-rates: 1 Mbps, 1.4 Mbps, 1.8 Mbps, 2.2 Mbps and 2.6 Mbps, which cover a wide range of values real multimedia streaming would use in various delivery conditions. Table I shows the number of clients receiving multimedia content considered in each simulation scenario, their bit-rate as allocated by QOAS and the corresponding average throughput, packet loss and packet delay. The test video clips were encoded at the above mentioned bit-rates using the standard video encoder used by QOAS with uniform compression level adjustment (which will henceforth be called the CONSTANT adaptive scheme) and the ROI-based encoder used by ROIAS with logarithmic and linear bit-rate adjustments schemes (which will be refered to as Linear-ROIAS and Logarithmic-ROIAS, respectively).

A. Multimedia Clips

Nine multimedia clips were used for the objective as well as subjective multimedia quality assessment tests. The clips are between 25s and 40s long, with a frame rate of 25fps and a resolution of 640 x 480 pixels. They were selected based on their content characteristics in terms of type of content and spatial and temporal complexity. A detailed description of these clips can be found in [1].

Fig. 3 presents images taken from the nine clips used for ROIAS performance evaluation. Each clip contains different types of content with different degree of movement.

B. Objective Video Quality Assessment

The performance of ROIAS is evaluated by assessing the video quality of the test clips encoded at different bit-rates as previously described. As there is not a video quality metric which research community agrees that fully reflects user QoE, video quality was objectively assessed in terms the following metrics: PSNR, VQM and SSIM. MSU Video Quality Measurement Tool [58] was used to perform the testing.

PSNR, although the most widely used objective video quality metric, is reported not to correlate well with viewer perceived quality, especially when assessing the quality of video transmissions which are affected by variable loss [50]. VQM has been found to have a good correlation with subjective quality ratings for both standard and high definition television [59]. SSIM has been found to have better correlation with subjective ratings than PSNR and its performance is close in this respect with VQM [60] [53].

The goal of the objective testing was to compare the CONSTANT adaptation approach during streaming which affected the whole frame area equally with the two versions of ROIAS: Linear-ROIAS which affects linearly the quality of the content during adaptive streaming as it is located further from the AMUI and Logarithmic-ROIAS which adjusts content quality logarithmically in relation to its distance from the AMUI.

C. Subjective Video Quality Assessment

The video clips were assessed by 66 users using the Quality of Perception (QoP) metric and methodology described in [1]. To counteract order effects, each user saw the nine video clips in a randomized order, with three of the clips being coded with the CONSTANT method, Linear-ROIAS, and Logarithmic-ROIAS methods, respectively. The particular coding employed

TABLE I
CONTENT DELIVERY SIMULATION RESULTS.

	Clients distribution over target bit-rates					Quality of Service		
Clients	1.0 Mbps	1.4 Mbps	1.8 Mbps	2.2 Mbps	2.6 Mbps	Avg. Thr. (Mbps)	Avg. Loss (%)	Avg. Delay (ms)
90	66	24	0	0	0	1.07	2.34	9.4
85	48	37	0	0	0	1.15	0.86	9.4
80	41	28	11	0	0	1.22	0.99	9.4
75	34	21	20	0	0	1.30	0.68	9.3
70	22	25	23	0	0	1.39	0	9.3
65	14	21	24	6	0	1.51	0.39	9.3
60	9	15	27	9	0	1.62	0	9.2
55	0	11	31	13	0	1.80	0	9.2
50	0	12	14	11	13	1.98	0.19	9.3
45	0	7	8	10	20	2.17	0	9.3
40	0	0	2	7	31	2.47	0	9.2
35	0	0	0	0	35	2.59	0	9.1

was unknown to the user. As part of the QoP methodology, after viewing each such clip, the user is asked to indicate his/her subjective satisfaction with the quality of the video clip on a Likert scale of 1-5. This scale is used in our analysis.

The Likert scale is widely used in sociological and behavioural sciences and indicates the strength of feeling that an individual has with respect to a statement targeting a particular issue of interest to the researcher. In our case, the scale was anchored at 1= "Very Poor" and 5="Excellent".

V. RESULTS ANALYSIS

The performance of ROIAS was assessed using both objective metrics and subjective methods and the results were compared with the ones achieved by the CONSTANT adaptation technique which is an adaptive streaming solution which adjusts uniformly the bit-rate over the entire picture area.

A. ROIAS Objective Quality Assessment

The performance of ROIAS was objectively assessed using three distinct objective video quality metrics: PSNR, VQM and SSIM. Fig. 4, Fig. 5 and Fig. 6 graphically presents the scores of objective video quality assessment achieved by the means of the three metrics mentioned above, performed on the whole image area, with test clips encoded at 1.0Mbps, 1.8Mbps and 2.6Mbps respectively.

Although the average values show a decrease or an insignificant improvement in terms of video quality when comparing both Linear-ROIAS and Logarithmic-ROIAS with the CONSTANT scheme analysis of the quality scores for each video clip used for testing separately shows that in some cases Logarithmic-ROIAS performs better than the other two. This can be observed in Fig. 4, Fig. 5 and 6. These three figures show the PSNR, VQM and SSIM scores achieved by the three adaptation schemes discussed for each test video clip separately. Note that lower VQM scores mean better video quality.

Consequently we performed a statistical analysis of variance (ANOVA) [61] on the results to evaluate if there is a significant difference between the video quality scores achieved by the

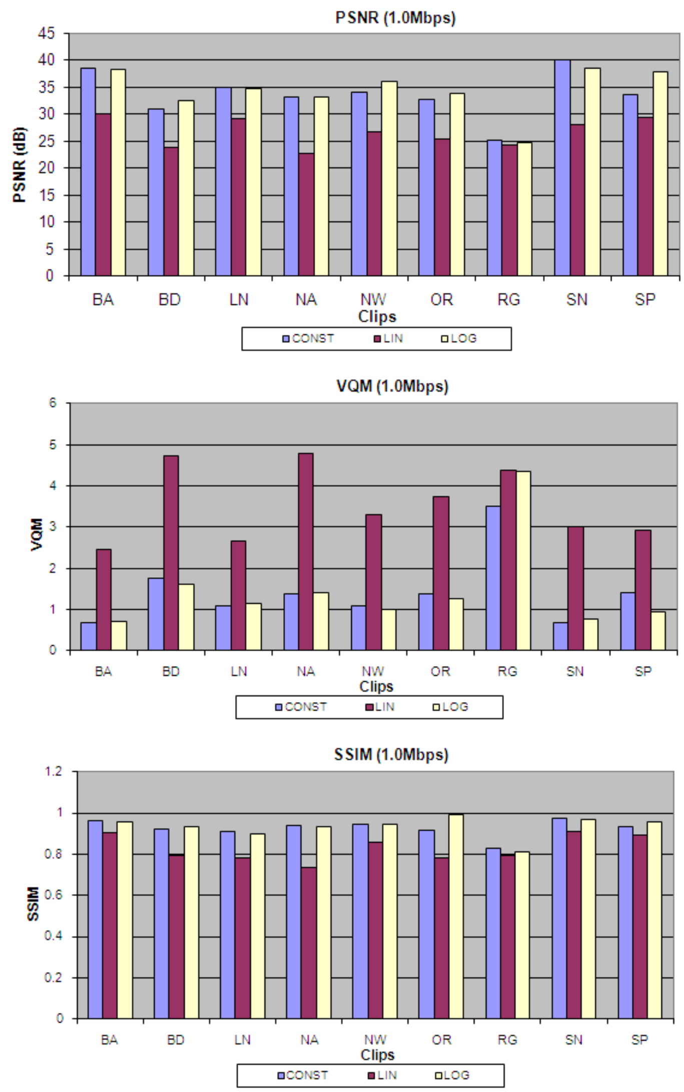

Fig. 4. Objective video quality assessment for the nine video clips encoded at 1.0Mbps

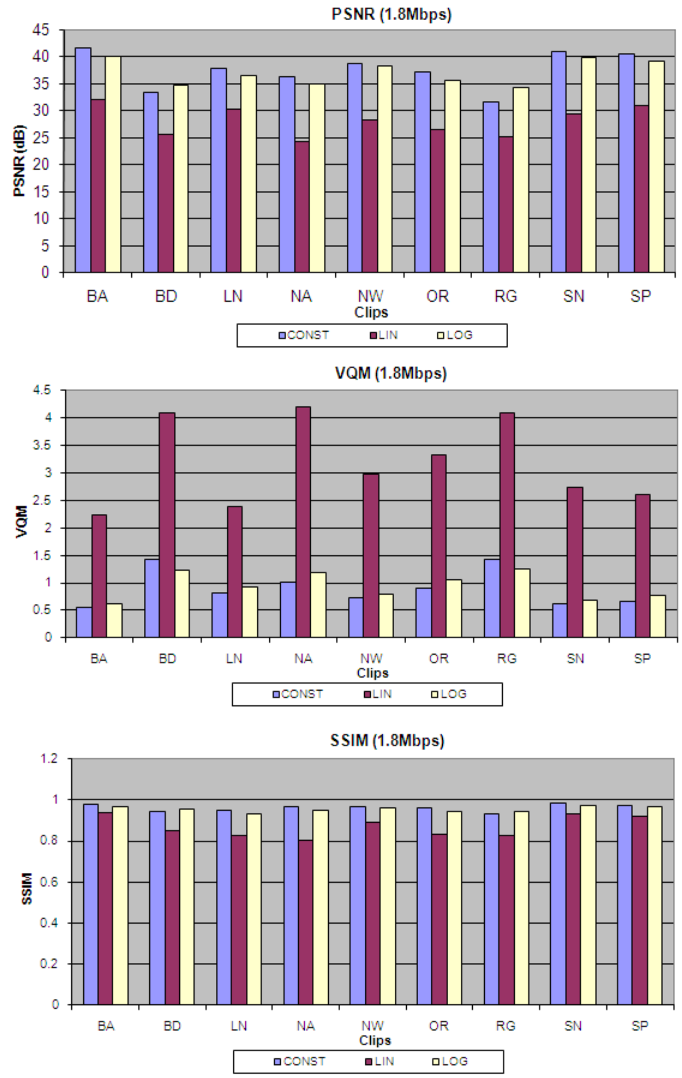

Fig. 5. Objective video quality assessment for the nine video clips encoded at 1.8Mbps

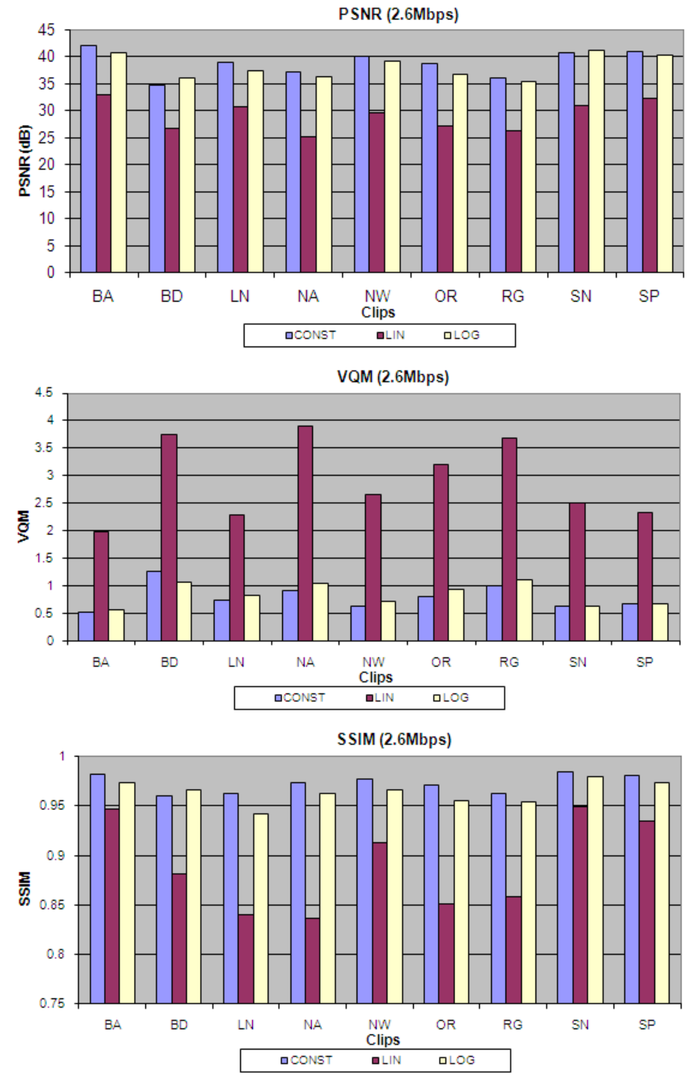

Fig. 6. Objective video quality assessment for the nine video clips encoded at 2.6Mbps

adaptation schemes discussed. To determine which adaptive scheme performs better and in which conditions multiple comparison tests were performed based on Games-Howell procedure and when homogeneity of variance could be verified Tukey HDS was used as well.

Statistical analysis performed on the PSNR, VQM and SSIM scores achieved by applying these metrics on the whole image area revealed that Linear-ROIAS performs significantly worst then the other two adaptive schemes (i.e. Logarithmic-ROIAS and CONSTANT adaptation). However, there was no significant difference between Logarithmic-ROIAS and the CONSTANT scheme to conclude on which one performs best from the point of view of objective video quality metrics. Nonetheless, statistical analysis performed on the PSNR, VQM and SSIM scores achieved by applying these metrics on the AMUI revealed that Logarithmic-ROIAS and Linear-ROIAS performs better than CONSTANT especially when low bit-rates are required. For a more detailed analysis of the objective testing results please refer to [16].

B. ROIAS Subjective Quality Assessment

Fig. 7 presents the user satisfaction expressed in terms of Mean Opinion Score (MOS) for the video streams encoded at 1Mbps, 1.8Mbps and 2.6Mbps, respectively. It can be clearly noted that the values are quite scattered, being impossible to estimate which adaptive scheme performs the best in terms of user satisfaction. The same variation in user satisfaction was encountered when the clips are encoded at 1.4 Mbps and 2.2 Mbps. Consequently the statistical analysis of variance (ANOVA) [61] was performed on the subjective testing results achieved by each adaptive scheme using SPSS.

Table II presents the average results of subjective video quality assessment from SPSS when performing ANOVA on the subjective assessment results grouped by test clip bit-rates. Two aspects were considered: user satisfaction and information assimilation. The results of ANOVA show that there is significant difference between the results obtained with different schemes in terms of user satisfaction. The F value is high ($F = 16.393$) showing that the variation among the

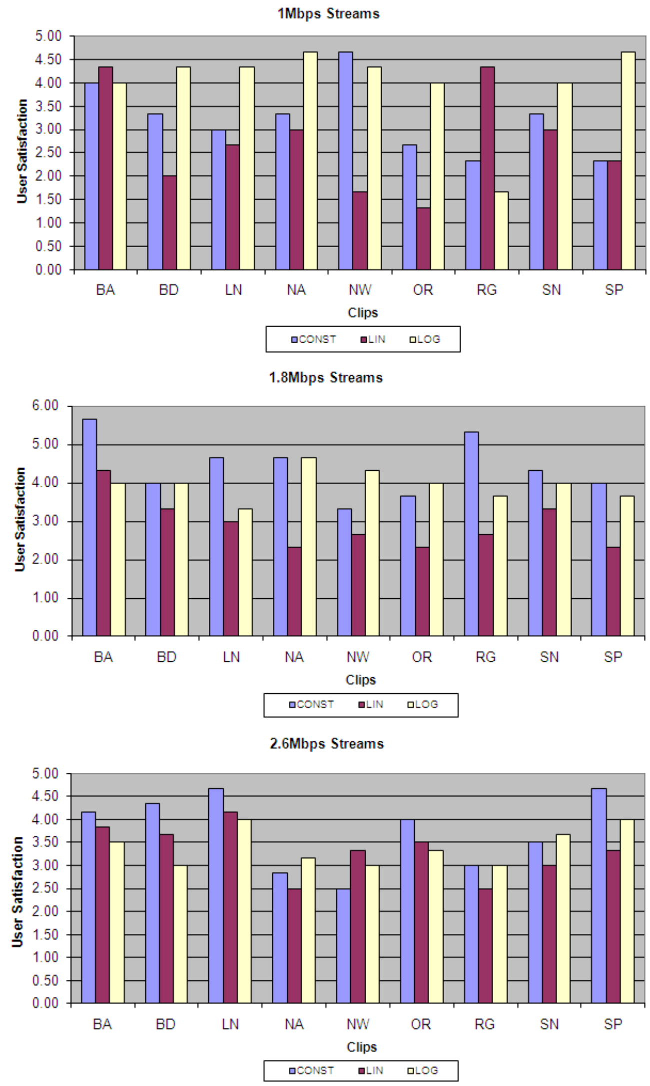

Fig. 7. User satisfaction scores for the nine video clips encoded at 1Mbps, 1.8Mbps and 2.6Mbps

assessed group members is higher than what can be expected to be seen by chance. The p value is small ($p < 0.05$) showing that it can be said with 95% accuracy that the results obtained are not due to random sampling.

As there is no significant impact on information assimilation, consequently the following analysis will focus on user satisfaction only.

Fig. 8 shows the average user satisfaction for each adaptation scheme separately and for each distinct clip bit-rate used for testing as well as the overall average.

Relying on average values only is not enough to reach a conclusion regarding the performance of the three adaptation schemes discussed. To this end, comparison tests were performed based on Games-Howell and when homogeneity of variance could be verified, Tukey HDS was used as well.

Results showed that significant differences appeared especially for the low bit-rate streams with Logarithmic-ROIAS performing better than the CONSTANT adaptive scheme while Linear-ROIAS showed significant lower performance than the other two. However in certain situations such as in the context of high motion video content (i.e. moving camera) as in clip RG when the background is naturally blurred, the users will not perceive the negative effect of Linear ROIAS outside the area of maximum user interest. Hence, better performance of Linear ROIAS is achieved when low bit-rate (1.0 Mbps) is used. These results are in concordance with the means presented in Fig. 8.

TABLE II
SUBJECTIVE VIDEO QUALITY ASSESSMENT (MOS).

	CONSTANT		LIN-ROIAS		LOG-ROIAS	
bit-rate	Satisf.	Assim.	Satisf.	Assim.	Satisf.	Assim.
1.0 Mbps	3.22	62.74	2.74	60.63	4.00	63.70
1.4 Mbps	3.00	47.67	3.63	45.48	4.30	52.37
1.8 Mbps	4.41	61.59	2.93	61.63	3.96	62.93
2.2 Mbps	3.74	54.67	2.70	50.26	3.81	50.07
2.6 Mbps	3.74	57.19	3.31	50.00	3.41	55.81

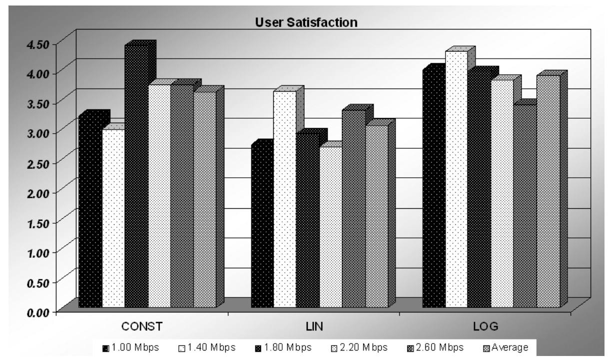

Fig. 8. Average user satisfaction for individual bit-rates and overall

C. Objective-Subjective Assessment Results Comparison

As presented in the previous sections the objective quality assessment methods showed that Linear-ROIAS perform worst that the other two methods when the whole image area is considered. The same result was reached when objective testing was performed on the same test video clips. In the same time both Logarithmic-ROIAS and Linear-ROIAS offers better quality in the AMUI region than the CONSTANT scheme. This demonstrates that Linear-ROIAS degrades more rapidly and intensively the regions furthest from the AMUI which is negatively perceived by the user although the area which receives maximum user interest shows better image quality.

The objective video quality assessment did not give a clear verdict regarding the performance of Logarithmic-ROIAS and CONSTANT techniques, although in terms of AMUI Logarithmic-ROIAS performs better. The clarification came from the subjective testing, where Logarithmic-ROIAS showed better performance than both Linear-ROIAS and the CONSTANT method.

Comparing the results of the statistical analysis performed on both subjective and objective testing shows that the region of interest plays and important role in maintaining a high level of user quality of perception. However the video quality levels

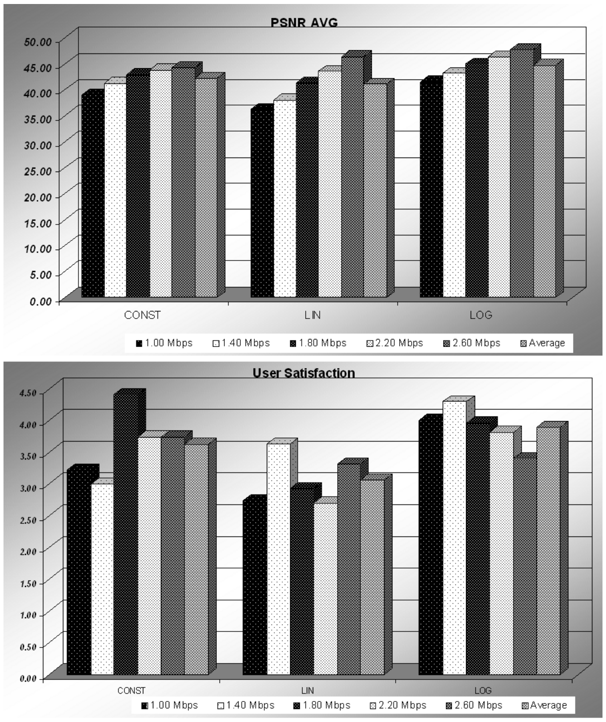

Fig. 9. Average user satisfaction for individual bit-rates and the overall mean compared with the mean between average PSNR rates for the whole image area and the average PSNR rates for AMUI

of the areas further from the AMUI have to be kept above a certain minimum quality to avoid negative impact on user QoP.

This conclusion is backed up by the fact that Linear-ROIAS, which degrades more drastically the areas furthest from user's point of gaze presents high quality improvements in the AMUI area (up to 72%) compare to Logarithmic-ROIAS (up to 42%). However when subjective video quality assessment is performed the statistical analysis shows significant decrease in overall user perceived quality encountered by Linear-ROIAS compared with Logarithmic-ROIAS and the CONSTANT scheme.

Fig. 9 presents the average user satisfaction for individual bit-rates and the overall mean compared with the mean between average PSNR rates for the whole image area and the average PSNR rates for AMUI. This shows that by averaging the PSNR scores for the whole image area with the PSNR scores achieved excursively by comparing the AMUI areas the objective video quality trend becomes increasingly similar with the one determined by user satisfaction.

VI. Conclusions and Future Works

The Region of Interest-based Adaptive multimedia Streaming scheme (ROIAS), unlike most existing adaptive multimedia streaming solutions considers the user point of gaze in the adaptation process. Two flavors of ROIAS are evaluated in terms of user quality of perception assessed by both objective video quality metrics and subjective methods.

As most of the work in the area of user perceived multimedia quality uses either subjective or objective techniques to assess video quality the comparative analysis of both types of results is a major contribution brought by this paper.

The comparative analysis of subjective and objective video quality assessment results shows that considering user region of interest in bit-rate adaptation process increases the user perceived quality or user QoE especially when low bit-rates are required. However the dependency between the compression level and the distance to the area of maximum user interest is very important. Moreover, subjective testing has shown excessive quality degradation of areas furthest away from the area of maximum user interest has a negative impact on the user perceived video quality.

In conclusion, Logarithmic-ROIAS performs best and is recommended to be used especially when low bit-rates are required, in which case this ROIAS flavor presented video quality improvements up to 43% compared to traditional adaptation schemes.

Linear-ROIAS shows good video quality in the area of maximum user interest, with gains of up to 72% when high bit-rates are required. However due to the fact that it drastically increases the compression level for areas furthest from AMUI Linear-ROIAS shows significant decrease in overall video quality. Consequently this ROIAS flavor is recommended only for high bit-rates and when a significant high quality is required for the AMUI.

Future work will analyze the behavior of ROIAS multimedia adaptation scheme in relation to the type of content as well as image resolutions. Techniques for estimating the area of maximum user interest will be investigated and real-time perceptual testing will be performed. An additional study focusing on the effect of the AMUI size on user perceived quality and the impact of the resolution on the performance of ROIAS will also be part of future works.

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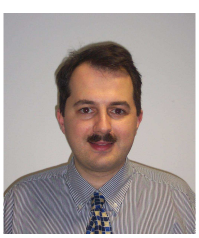

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