A New No Reference Metric for Estimation Video Quality Based on Blur Effect

Jean Nunes Ribeiro Araujo and Claudio de Castro Monteiro
e-mail: jean.to@gmail.com, ccm@ifto.edu.br
Network Computer Group - GREDES
IFTO Federal Institute of Education, Science and Technology of Tocantins
Palmas, Brazil

***Abstract*—The measurement and evaluation of video quality is a great challenge for real-time communication. Among those algorithms that evaluate the quality of video, many of them usually make use of reference the original video to compare pixel by pixel with the transmitted video. This fact makes the application of these algorithms complicated in real-time environments. Moreover, these algorithms based on structural similarity do not take into account human visual system information. This paper presents an algorithm that aims to assess the quality of a video sequence using the blurring effect based on human visual system information.**

Keywords-video; quality; metric; blur

I. INTRODUCTION

Streaming multimedia content is very sensitive to network conditions, especially in real-time transmissions. The noises introduced into an image in many instances are not perceived by the Human Visual System (HVS). Thus, packet loss and delays may not influence decisively the level of video quality perceived by the viewer. Human perception tends to tolerate more visual distortions since the images have an acceptable level of comprehension. Therefore, the concept of Quality of Experience (QoE) is essential for the development of models for measuring video quality [8], [9].

There are two different ways to calculate the quality of video transmitted over a network. The subjective tests are based directly on visual perception of the viewer, while the objective tests attempt to estimate the quality of a video without the direct intervention of the viewer, simulating the Human Visual System.

The subjective test is known as Mean Opinion Score (MOS) and has higher cost of implementation because it requires adequate space, specific technological resources, planning time and viewers in good eye health. However, the subjective test is presented as more reliable technique to human perception of quality. The recommendation BT. 500-11 ITU-R has specific procedures to perform the subjective tests [6].

Another way is through objective tests. The greatest interest of a metric objective is to be able to replace subjective tests, which are more expensive. Recent surveys show that the objective metrics that consider widely the Human Visual System have better results.

Most objective metrics are Full Reference (FR) or Reduced Reference (RR), only some are Null Reference (NR) [10], [11].

FR metrics determine the quality by comparing the images pixel by pixel of video transmitted over the corresponding images of the original video. RR metric selects some information from both video, and compares to obtain the quality threshold. NR metrics measure quality based on the video itself without receiving any information of the original video.

One of the best known metrics for objective evaluation is the Peak Signal Noise Ratio (PSNR). PSNR is the ratio between the input and output of a lossy compression process, which assesses how much compression added noises in the original image. Therefore, to perform the calculation, one needs to compare the original video and the video transmitted, featuring then a FR metric [1].

The metric PSNR has been widely used and has proven useful in many papers. However, it is not entirely reliable, especially because it takes into account the Human Visual System [10], [12].

In real-time environments it is clearly not feasible to have the original video as a parameter for measuring quality, thus justified the importance of NR metrics.

This paper aims to propose a NR metric for estimating video quality by using the artifact blurring in transmissions in real time [3].

Section 2 presents the description of the metric estimation of video quality using the blurring artifact and the conception of the algorithm. Section 3 illustrates the environment and details the methodology of the experiments. Section 4 describes the analysis of the results obtained in the experiments, highlighting the impact of QoS metrics have on the blur metric, and demonstrate the performance of this metric over the visual quality of the frames. Prediction models are defined in Section 5; the NR blur metric is taking as input the values of the variables of QoS. Section 6 presents the conclusion of our work and final remarks.

II. DESCRIPTION OF BLUR METRIC

Blur effect is caused by a loss of the high frequency content and can occur when we have video sequences, which characterizes well the video streams in a network environment.

 ISBN: 978-1-61208-284-4

In this sense, the estimate of the degree of blurring suffered by a sequence of frames can greatly influence the video quality and be able to demonstrate the current state of a network through the relationship with the QoS metrics. Therefore, the reverse is true if there is a coherent correlation between the metric and QoS metrics jitter, delay and loss.

To find this correlation we must first understand how the blur effect is perceived by people. When comparing a sharp image with this same image blurred, human perception detects a significant difference in terms of loss of detail between the first and second image. However, if we compare an image already blurred and the same image further blurred the difference between the two can be small. This situation is depicted in Fig. 1.

Figure 1. From left to right: original frame, frame transmitted with limited 100Kbps, frame transmitted with limited 50Kbps

An important detail is that, when observing an image containing a small part blurred over a homogeneous area, human perception identifies that the image is blurred, even if only a small part is blurred. For this reason, the analysis of the variation of neighboring pixels, the blurring metric considers only the pixels that have changed after the process that causes the uncomfortable image in [3]. In this sense, the main idea is to determine the degree of blurring suffered by frame, compared to a previous frame.

Considering the phenomena explained, it is then possible to quantify the discomfort caused by the blur effect in a video frame. The first step consists of calculating the metric in determining the variations in intensity between neighboring pixels of an initial frame. Then, calculate the variations between neighboring pixels of the next frame and compare the variations of intensity of the initial frame and the next frame, allowing to evaluate the nuisance blur effect between the two frames.

Thus, a greater variation between the initial frame and the next frame means that the initial frame was clear. However, if there is less variation between the original frame and the next frame means that the initial frame was already blurred. This description is summarized in Fig. 2.

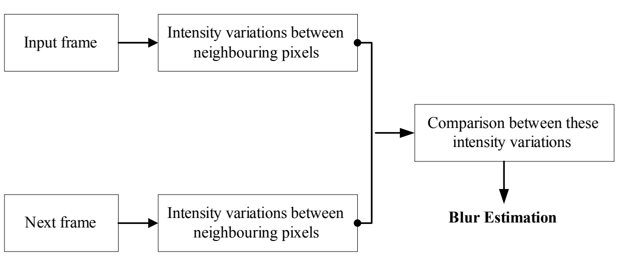


Figure 2. Simplified flow-chart of the blur estimation principle

Importantly, the metric uses frames that were transmitted from the server to the client, not requiring the use of the original video to analyze video quality, unlike the PSNR metric that needs the original frames of reference. Therefore, this estimation of blurring is characterized as a method of gauging the video quality without reference.

This feature eliminates the inconsistency problem that can occur using the PSNR, which may be caused by losses in the transmission frames, which in many cases causes a loss of reference for calculating the quality of certain frames [3].

It is, then, necessary to analyze the variation of neighboring pixels. If this variation between the two frames is high, the initial frame has a higher degree of sharpness. Therefore, in order to represent the degree of blurring, the result is normalized within the defined range between 0 and 1, which are respectively the best and worst quality in terms of perceived blurring. Based on the concepts and equations described in [3] was possible to adapt the metric in the form of algorithm running within an environment of streaming video on demand, returning the value of blurring each frame, allowing the achievement of threshold quality of the video as a whole.

We used a function written in GNU Octave [13], developed for mathematical computation. Initially, we used an implementation of the blurring of perception developed in MATLAB described in [3] and adapted their execution in Octave, in order to insert a loop for process all frames in video sequence.

The original function returns the value of blurring only comparing the original image with a blurred image. As in our model we want to perform video transmission, it was necessary to adapt the metric to function within a repeating structure that calls the function for each frame received by the client.

After transmission of the video in the network, we need to transform the mp4 video received by the user into png images and then execute the program that calculates the blurring.

With these frames stored in a folder, we can change the algorithm of perceived blurring to obtain the quality of each frame. Thus we call the function that calculates the blurring comparing the current frame to the next frame, for later analysis.

III. METHODOLOGY

The structure of the test environment was built with the goal of providing adequate conditions for implementation of multimedia streams, in order to facility the assessment of that the network quality of services causes in the video quality reception.

The physical layout and functionality of computers followed the recommendation G. 1082 ITU-T described in [7], which defines well most environments used in research of this nature. We used four netbooks prepared as described

 ISBN: 978-1-61208-284-4

in Fig. 3; each netbook played certain roles within the proposed scheme.

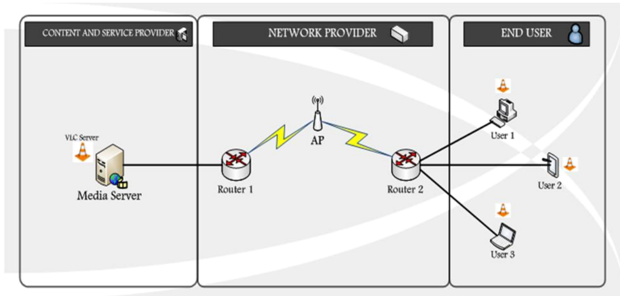
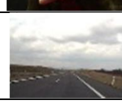


Figure 3. Environment execution of experiments

In the environment we have a media server that delivers content on demand to customers via VLC server. The core network consists of two routers that communicate with each other through a WLAN 802.11g. The video streams stored in the Content Provider and Service Provider are sent via the Network and viewed by End-User. In the user's host is deployed a testbed for optimization and automation of media requests and data collection regarding network transmission and video.

The hosts running the Linux operating system Ubuntu 11.04. The other programs used in the experiments are all based on free software. The videos were encoded in H264/MPEG4 using 300Kbps bitrate and GOP size 12 obtained in [2]. The characteristics of videos used are described in Table I.

TABLE I. DESCRIPTION OF VIDEO SEQUENCES USED IN TRANSMISSIONS

Video	Info	Image
elephants_dream	3500 frames 120 seconds 16:9	
highway	2000 frames 120 seconds 4:3	

The experiments were composed of 4 test groups categorized by the band width limitation imposed on the network for multimedia streams, as shown in Table II.

TABLE II. GROUP OF EXPERIMENTS DEFINED FROM THE BANDWIDTH LIMITATION IMPOSED ON THE NETWORK

Group of experiment	Multimedia traffic limited to:
Group 01	50 Kbps
Group 02	100 Kbps
Group 03	300 Kbps
Group 04	500 Kbps

To determine the sample size needed for population results presented 95% confidence, a sample was defined model of 10 broadcasts each video stream, in order to assess statistical data from the results. We use a bandwidth limitation for multimedia transmission of 50Kbps, characterized as the worst in our proposal.

Thus, we found the mean and average standard deviation of each population parameter used. Analyzing the results, the delay showed the values of standard deviation higher, so the estimate of the ideal size of population was based on this metric.

Thus, in each group, we executed the 3 video streams described, 135 transmissions for each stream, totaling 270 transmissions/group and 1080 overall transmissions. For each group of experiments, we observed variable values of delay, jitter, and packet loss during transmission of each video stream in order to identify and analyze the impacts of these parameters on video quality NR blur metric.

IV. RESULTS

Based on these procedures, we analyzed the data obtained in the transmission, where it was possible to find the boundary values for each parameter raised to a video that can be delivered with quality customer service. The information collected in each test group used to calculate statistically the influence that each has on QoS metrics to measure objectively without reference BLUR. This determination makes it possible to predict video quality based on network conditions, by analyzing correlations between QoS and variable QoV BLUR.

Based on what was described in the previous section, it was determined that the samples used in each assay were 135 repeats for each video sequence mounted on the environment. To the test groups, the average values of delay, jitter, packet loss, and BLUR were computed for transmission. After the 135 transmissions, the average values for the variables were calculated, establishing a confidence interval for these values, with a significance level of 95%, achieving a margin of error depending on the average standard deviation of each variable examined and the sample size population under consideration.

The blur metric values are shown through Figures 4, 5, 6, 7, 8, 9, 10, and 11. The details of the results of QoS metrics and blur metric are described in Tables III, IV, V, VI, VII, VIII, IX, and X.

A. Group 1 (50 Kbps)

In Figures 4 and 5, we can observe the values of the metric blur in the 135 transmissions performed for both video sequences, subject to the limitation 50Kbps. In this scenario, we can say that the network is in a situation poorly suited for performing multimedia streams, which reflects negatively on the values of delay, jitter, and loss shown in Tables III and IV. The average delay measured exceeded 2000ms for both sequences.

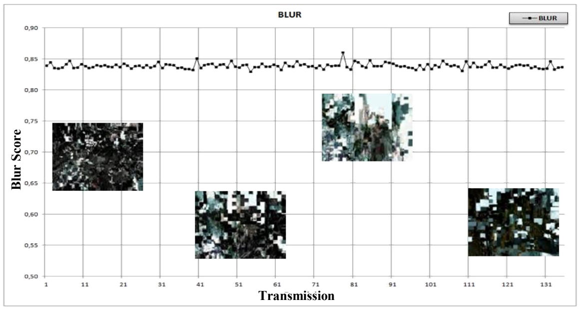


Figure 4. Elephants_dream Blur Score

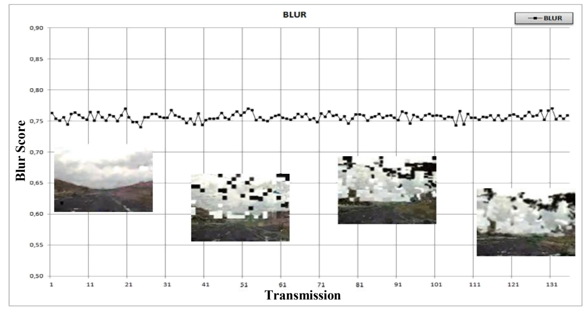


Figure 5. Highway Blur Score

TABLE III. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS AND, BLUR FOR GROUP 01 FOR VÍDEO ELEPHANTS_DREAM

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	2308.50	122.91	15.90	0.8387
Max	2388.28	144.46	24	0.8601
Min	2056.07	92.04	7	0.8291
DP	83.38	11.17	3.61	0.0042
Error	14,06	1.88	0.61	0.0007
Assurance Interval	2294.43 – 2322.56	121.03 – 124.80	15.30 – 16.51	0.8380 – 0.8394

TABLE IV. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS, AND BLUR FOR GROUP 01 FOR VÍDEO HIGHWAY

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	2272.78	153.56	10.97	0.7564
Max	2394.24	201.43	21	0.7701
Min	1878.42	103.50	4	0.7399
DP	150.03	16.81	3.01	0.0058
Error	25.3078	2.8361	0.5073	0.0010
Assurance Interval	2247.47 – 2298.09	150.72 – 156.39	10.46 – 11.48	0.7554 – 0.7574

The values of packet loss showed variation due to the characteristics of the video. The first sequence has a larger number of frames, which often change during transmission. So, the average loss was larger than the other sequence.

This fact is observed by the four frames extracted, reflected in the averages of the metric without reference BLUR. By analyzing the blur metric, we conclude that the quality of streaming videos is unsatisfactory for any viewer. However, the sequence *elephants_dream* showed a worse state, as described by the blur metric value, which reached a maximum value of 0.8601 and an average of 0.8387, values nearly 10% higher than the other sequence.

B. *Group 2 (100 Kbps)*

In Figures 6 and 7, we can observe the values of the metric blur in the 135 transmissions performed for both video sequences, subject to the limitation 100Kbps. In this scenario, there were improvements in the conditions of the network, but not enough to assert that the state was suitable for performing multimedia streams. The average delay measured exceeded 1000ms for both sequences.

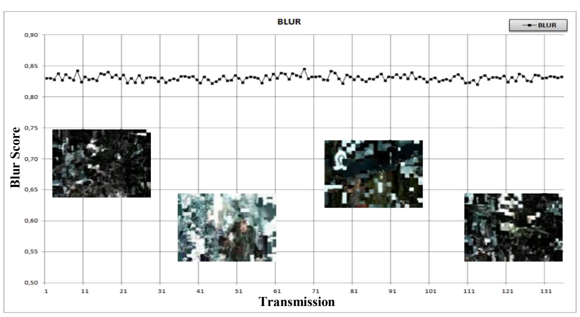


Figure 6. Elephants_dream Blur Score

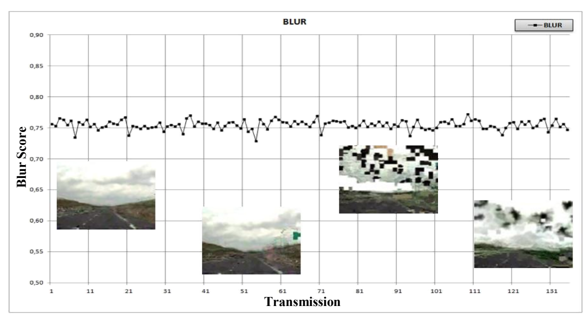


Figure 7. Highway Blur Score

TABLE V. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS, AND BLUR FOR GROUP 02 FOR VÍDEO ELEPHANTS_DREAM

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	1160.99	60.11	9.526	0.8308
Max	1189.97	74.26	20	0.8453
Min	1010.88	46.06	2	0.8200
DP	39.51	5.19	3.032	0.0048
Error	6.66	0.87	0.51	0.0008
Assurance Interval	1154.33 – 1167.66	59.24 – 60.99	9.02 – 10.04	0.8300 – 0.8316

TABLE VI. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS, AND BLUR FOR GROUP 02 FOR GROUP 01 FOR VÍDEO HIGHWAY

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	1147.01	77.12	6.50	0.7549
Max	1199.37	99.44	13	0.7720
Min	951.55	53.64	1	0.7287
DP	59.02	8.52	2.29	0.0073
Error	9.96	1.44	0.39	0.0012
Assurance Interval	1137.06 – 1156.97	75.68 – 78.55	6.12 – 6.89	0.7537 – 0.7561

Again, the values of packet loss were higher in the sequence *elephants_dream*. The improved values of QoS metrics is not sufficient to promote a significant increase in the quality of the videos, which was adequately demonstrated by the metric blur.

C. Group 3 (300 Kbps)

In Figures 8 and 9, we can observe the values of the metric blur in the 135 transmissions performed for both video sequences, subject to the limitation 300Kbps. In this scenario, the packet loss in the network reduces to a value close to zero, since the video was encoded with bitrate 300Kbits and therefore found better conditions for transmission.

Thus, with the loss, the other variables network also decrease. We can see more clearly in the frames extracted from sequences, demonstrated in a value of blur metric, which showed lower averages compared to the first two groups. The highway sequence adapted better network conditions by having fewer frames and little variation between the images, showing an average of 0.6787 blur metric.

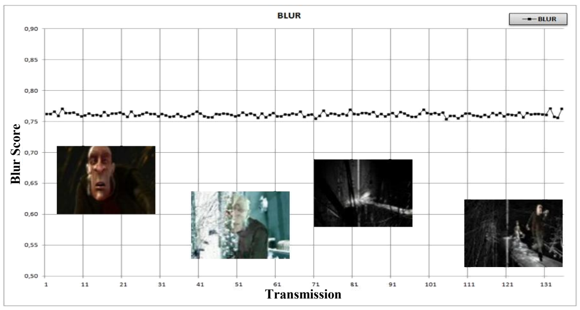


Figure 8. Elephants_dream Blur Score

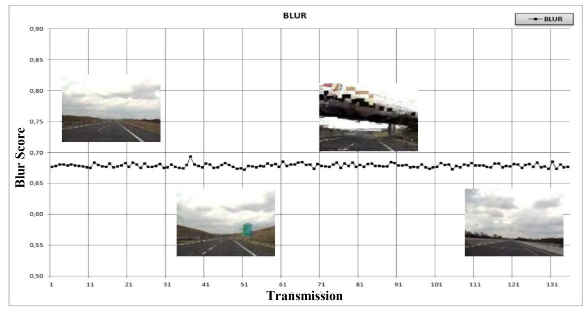


Figure 9. Highway Blur Score

TABLE VII. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS, AND BLUR FOR GROUP 03 FOR VÍDEO ELEPHANTS_DREAM

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	241.27	56.41	1.56	0.7615
Max	247.46	61.26	5	0.7712
Min	234.28	46.91	0	0.7537
DP	3.11	2.58	1.22	0.0031
Error	0.52	0.44	0.21	0.0005
Assurance Interval	240.75 – 241.80	55.97 – 56.84	1.36 – 1.77	0.7610 – 0.7620

TABLE VIII. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS, AND BLUR FOR GROUP 03 FOR GROUP 01 FOR VÍDEO HIGHWAY

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	313.84	52.98	1.12	0.6787
Max	341.85	69.16	4	0.6931
Min	285.35	46.72	0	0.6723
DP	9.75	3.91	0.94	0.0031
Error	1.64	0.66	0.16	0.0005
Assurance Interval	312.20 – 315.49	52.32 – 53.64	0.96 – 1.28	0.6781 – 0.6792

D. Group 4 (500 Kbps)

In Figures 10 and 11, we can observe the values of the metric blur in the 135 transmissions performed for both video sequences, subject to the limitation 500Kbps. This scenario presents conditions much more suitable for video traffic on the network, significantly reducing the variable values of QoS. With the average delay and jitter less than 15ms, packet loss reduces to a level very close to zero, reflecting as expected the blur metric and sharpness of the images taken.

The *highway* sequence in this scenario presents values blur allowing qualify frames of videos as well sharp to the viewer. However, the *elephants_dream* sequence has higher average blur, demonstrating that the specific features of each video can cause variations in QoV metrics, even under identical conditions of traffic.

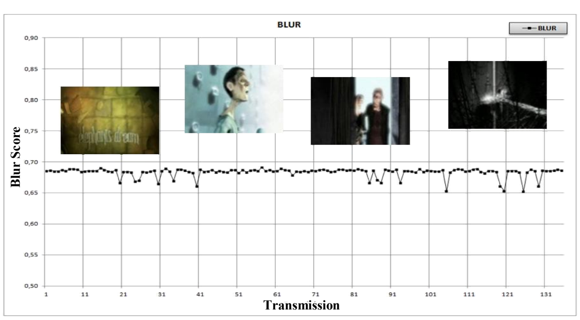


Figure 10. Elephants_dream Blur Score

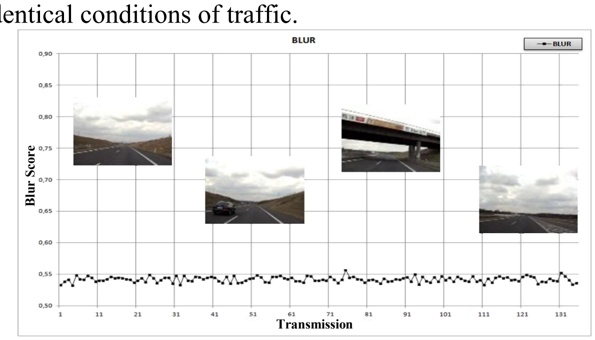


Figure 11. Highway Blur Score

TABLE IX. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS AND, BLUR FOR GROUP 04 FOR VÍDEO ELEPHANTS_DREAM

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	17.41	13.53	0.25	0.6832
Max	24.67	18.63	1	0.6912
Min	10.87	7.22	0	0.6525
DP	2.76	2.51	0.44	0.0076
Error	0.47	0.42	0.07	0.0013
Assurance Interval	16.94 – 17.87	13.10 – 13.94	0.18 – 0.32	0.6820 – 0.6845

TABLE X. AVERAGE, MAXIMUM, MINIMUM AND ASSURANCE INTERVAL MEASURED FOR DELAY, JITTER, LOSS AND, BLUR FOR GROUP 04 FOR GROUP 01 FOR VÍDEO HIGHWAY

	Delay (ms)	Jitter (ms)	Loss	Blur
Avg	12.29	12.80	0.09	0.5420
Max	106.96	56.85	2	0.5566
Min	5.74	4.44	0	0.5322
DP	10.71	6.49	0.31	0.0044
Error	1.81	1.09	0.05	0.0007
Assurance Interval	10.48 – 14.10	11.70 – 13.89	0.04 – 0.14	0.5413 – 0.5427

TABLE XI. ASSURANCE INTERVALS (AI) OF POPULATION PARAMETERS OF VIDEO ELEPHANTS_DREAM

Video: *elephants_dream*				
	AI – Delay	AI – Jitter	AI – Loss	AI – Blur
Group 01 (50Kbps)	2294.43 – 2322.56	121.03 – 124.80	15.30 – 16.51	0.8380 – 0.8394
Group 02 (100Kbps)	1154.33 – 1167.66	59.24 – 60.99	9.02 – 10.04	0.8300 – 0.8316
Group 03 (300Kbps)	240.75 – 241.80	55.97 – 56.84	1.36 – 1.77	0.7610 – 0.7620
Group 04 (500Kbps)	16.94 – 17.87	13.10 – 13.94	0.18 – 0.32	0.6820 – 0.6845

TABLE XII. ASSURANCE INTERVALS OF POPULATION PARAMETERS OF VIDEO HIGHWAY

Video: *highway*				
	AI – Delay	AI – Jitter	AI – Loss	AI – Blur
Group 01 (50Kbps)	2247.47 – 2298.09	150.72 – 156.39	10.46 – 11.48	0.7554 – 0.7574
Group 02 (100Kbps)	1137.06 – 1156.97	75.68 – 78.55	6.12 – 6.89	0.7537 – 0.7561
Group 03 (300Kbps)	312.20 – 315.49	52.32 – 53.64	0.96 – 1.28	0.6781 – 0.6792
Group 04 (500Kbps)	10.48 – 14.10	11.70 – 13.89	0.04 – 0.14	0.5413 – 0.5427

In order to check the impacts of network conditions on each variable used, Tables XI and XII show the assurance intervals for each parameter of the sample population.

As can be observed, the variables delay, jitter, and loss exhibits values that vary depending of terms of limitation and traffic in network. The intervals of confidence show with clarity the differences between the Averages of each parameter for each video transmitted.

We also conclude that the metrics without reference BLUR translates well the quality of a video transmitted in a network based on state of middle of transmission, visa that the same if showed sensitive to variations at the limitations and in incidence of traffic competitor ally to character specific of each sequence of video.

V. PREDICTION MODELS OF BLUR METRIC

Considering a linear relationship between the variables of QoS (delay, jitter, and packet loss) and the Blur metric, we consider a linear model of blur prediction expressed by equation (1).

$$Y=b_0+ b_1.x_j+ b_2.x_a+b_3.x_p \tag{1}$$

where, Y = Blur Estimated;
b_0 = Coeficient of adjustment linear;
b_1 = Coeficient of jitter;
x_j = Value average of jitter;
b_2 = Coeficient of delay;
x_a = Value average of delay;
b_3 = Coeficient of loss;
x_p = Value average of loss;

With the goal of checking the degree of influence that each variable of QoS exercises about the blur metric, mathematical models were developed using multiple linear regression. As output, we obtain the estimate of blur in function of variables delay, jitter, and loss, using as input the values collected in the groups of experiments described in the previous session. Within this context, we consider that the variables of QoS act together and identify the state of the network, thus the thresholds of blur are dependent on these metrics. This is expressed through a linear system of equations into (2).

$$\begin{bmatrix} n & \sum_{i=1}^{n} x_{ji} & \sum_{i=1}^{n} x_{ai} & \sum_{i=1}^{n} x_{pi} \\ \sum_{i=1}^{n} x_{ji} & \sum_{i=1}^{n} x_{ji}^2 & \sum_{i=1}^{n} x_{ai}x_{1i} & \sum_{i=1}^{n} x_{3i}x_{ji} \\ \sum_{i=1}^{n} x_{ai} & \sum_{i=1}^{n} x_{ji}x_{ai} & \sum_{i=1}^{n} x_{ai}^2 & \sum_{i=1}^{n} x_{3i}x_{ai} \\ \sum_{i=1}^{n} x_{pi} & \sum_{i=1}^{n} x_{ji}x_{pi} & \sum_{i=1}^{n} x_{2i}x_{pi} & \sum_{i=1}^{n} x_{pi}^2 \end{bmatrix} . \begin{bmatrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{bmatrix} = \begin{bmatrix} \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_{ji}y_i \\ \sum_{i=1}^{n} x_{ai}y_i \\ \sum_{i=1}^{n} x_{pi}y_i \end{bmatrix} \tag{2}$$

The coefficients b_0, b_1, b_2, and b_3 represent the impact that each variable of QoS exercises on result of blur metric and were obtained through the Gauss-Seidel iterative method [14] for solutions of linear equations, using k = 8 iterations for each group of experiments.

After the 8 iterations, 8 values for the coefficients were found; they were used in each of 4 groups, to estimate the values of blur. This form the 8 values of blur estimated for each group, were compared with those obtained experimentally, in order check whether the 8 sets of

 ISBN: 978-1-61208-284-4

coefficients obtained have more coefficient of determination.

Thus, the coefficients that presented more coefficient of determination were the ones chosen to complete the model of prediction of blur.

Using these models, it was possible to also determine equations of prediction generic independent of band limitation and network traffic for each video. For either, we obtained the averages of jitter, delay, loss, and blur for each group of experiments, and we apply over the results, the equations of prediction. Table XIII demonstrates the generic prediction equations for each video.

TABLE XIII. BLUR GENERIC PREDICTION EQUATIONS FOR EACH VIDEO

Video	Prediction Equation	Coefficient of determination
elephants dream	$Y = 0{,}00021780x_j + 0{,}00001082x_a + 0{,}00002303x_p + 0{,}73916$	0,9963362342
highway	$Y = 0{,}00014226x_j + 0{,}00003491x_a + 0{,}00079661x_p + 0{,}65460$	0,9994591652

Therefore, according to the values of the QoS metrics, it is possible, by means of these general equations, to determine the degree of blurring the video sequence suffered during transmission.

VI. CONCLUSION AND FUTURE WORK

The analysis of network quality is done using QoS metrics that describes, in practice, the current state of a computer network. These metrics (delay, jitter, and loss) are known well enough and used for purposes of determination of network overload. However, the values of QoS network variables don't shows a clear relationship with the quality of sequences multimedia transmitted over a computer network.

The ideal method is the subjective test, that sets the quality of agreement with the opinion of spectators. However, to implement this model of analysis, it requires a high cost in terms of technological and human resources. The PSNR objective metrics to determine the video quality still have particularities that generate some inconsistency; therefore, they are not fully reliable metrics.

In this context, we present a new prediction model for video quality, based on a no reference metrics, using blur estimate. We adapt and implement the metrics in a network environment, transmitting video sequences, in order to do several experiments that allowed to get information about the performance of metrics and analyze accordingly the data obtained.

We can conclude, based on results described in this work, that the metrics no reference of blur determination, it is demonstrated be an efficient method of video quality prediction, presenting correlation indexes very good in relationship to QoS variables. Beside this, we notice that the metrics has a very low computational cost, allowing its use in network selection solutions without incremental computational cost to mobile devices.

REFERENCES

[1] Q. Huynh-Thu and M. Ghanbari, “The accuracy of PSNR in predicting vídeo quality for different video scenes and frame rates,” Telecommunication Systems, pp. 35-48, 2012.

[2] Xiph, 2012. http://media.xiph.org/video/derf/, [retrieved: May, 2013]

[3] F. Crete, T. Dolmiere, P. Ladret, and M. Nicolas, “The BLUR effect: perception and estimation with a new no-reference perceptual blur metric,” Human Vision and Electronic Imaging XII, 64920I, 2007.

[4] H. Wu, K. Rao, and A. Kassim, “Digital video image quality and perceptual coding,” Journal of Electronic Imaging, 2007.

[5] A. Eden, “No-reference estimation of the coding PSNR for H. 264-coded sequences,” Consumer Electronics, IEEE Transactions, pp. 667-674, 2007.

[6] ITU-R Recommendation BT.500-11, “Methodology for the subjective assessment of the quality of television pictures,” In International Telecommunication Union, 2002.

[7] ITU-T, Recommendation G. 1082, “Measurement-based methods for improving the robustness of IPTV performance,” In International Telecommunication Union, 2009.

[8] C. Mingardi and M. Brunner, “IPTV Quality of Service Management in Home,” IEEE Communications Society, 2009.

[9] D. Migliorini, E. Mingozzi, and C. Vallati, “Performance evaluation of H.264/SVC vídeo streaming over mobile WiMAX,” Computer Networks – Vol. 55, pp. 3578–3591, 2011.

[10] C. Farias and A. Rodrigues, “Métricas objetivas para avaliação da qualidade de vídeo,” Simpósio Brasileiro de Sistemas Multimídia e Web – Webmedia, 2010.

[11] J. Cardoso, A. Mariano, C. Regis, and M. Alencar, “Comparação das Métricas Objetivas de Qualidade de Vídeos Baseadas na Similaridade Estrutural e na Sensibilidade ao Erro,” Revista de tecnologia da informação e comunicação, vol. 1, no. 2, pp. 33-40, 2012.

[12] C. Monteiro, “Um ambiente para apoio a integração de redes sem fio heterogêneas,” Tese de doutorado, Universidade de Brasília, 2012.

[13] GNU OCTAVE, 2013. http://www.gnu.org/software/octave/, [retrieved: June, 2013]

[14] R. Larson and D. Falco, “Elementary Linear Algebra,” Pennsylvania State University, Ed. 7, 2012.

 ISBN: 978-1-61208-284-4