A New Algorithm for Objective Video Quality Assessment on Eye Tracking Data

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Keywords: Video Quality Evaluation, Eye Tracking, No Reference Objective Metric.

Abstract: In this paper, we present an innovative algorithm based on a voting process approach, to analyse the data provided by an eye tracker during tasks of user evaluation of video quality. The algorithm relies on the hypothesis that a lower quality video is more "challenging" for the Human Visual System (HVS) than a high quality one, and therefore visual impairments influence the user viewing strategy. The goal is to generate a map of saliency of the human gaze on video signals, in order to create a No Reference objective video quality assessment metric. We consider the impairment of video compression (H.264/AVC algorithm) to generate different versions of video quality. We propose a protocol that assigns different playlists to different user groups, in order to avoid any effect of memorization of the visual stimuli on strategy. We applied our algorithm to data generated on a heterogeneous set of video clips, and the final result is the computation of statistical measures which provide a rank of the videos according to the perceived quality. Experimental results show that there is a strong correlation between the metric we propose and the quality of impaired video, and this fact confirms the initial hypothesis.

1 INTRODUCTION

Multimedia user experience evaluation is now an important topic of research, and it has been one of the most relevant since the early beginning of the multimedia content digitalization era. One of the crucial challenges in this field is defining quality assessment metrics, which had its explosion when the first image compression standards appeared. The proposal of new metrics for estimating the user perceived quality of a multimedia content, no matter if this content is an image, a video or an audio one, is increasing and refining each year. This study is the continuation of our previous work (Albanesi & Amadeo, 2011), which describes a new methodology to estimate the video perceived quality in case of lossy compression of a digital sequence. In that paper, the authors designed a subjective and no reference approach to measure the average ocular fixations duration of users subject to different quality level stimuli. These fixations were gathered through a set of experiments with the Eye-Tracker. We defined that a "temporal based" study, since the analysis algorithm of eye tracker data did not consider the position of the gaze, but only the durations of the fixations. The results obtained by the experimental procedure were elaborated to present a quantitative metric. It was proven that this metric has a good correlation with the user perceived video quality. The results encouraged us to think that a similar approach could be used not only to investigate time-related characteristics of the human ocular behavior on a video quality-assessing task, but also the space-related characteristics, i.e., the position of human eye fixation. We call these positions G*aze-Points*. Our proposal presents a voting-process based algorithm that works on Eye Tracker data to generate *Gaze-Maps*. On these maps, we compute statistical functions to generate a rank of video according to the measured perceived quality. Therefore, our method starts from subjective data (Eye-Tracker data) and generates an objective video quality metric. The elaboration of physiological Eye Tracked data returns a set of quantitative scores that allows ranking the stimuli accordingly to the perceived quality. Our final goal is to find a recurrent behavior of the HVS by computing quantifiable parameters that can help in discriminating video sets in relation to the user perceived quality. The paper is structured as follows: Section two includes a review of the state of the art of Multimedia Quality of Experience research and a

Grazia Albanesi M. and Amadeo R..
A New Algorithm for Objective Video Quality Assessment on Eye Tracking Data.
DOI: 10.5220/0004672104620469
In *Proceedings of the 9th International Conference on Computer Vision Theory and Applications* (VISAPP-2014), pages 462-469
ISBN: 978-989-758-003-1

conceptual comparison to our approach. Section three presents the new algorithm based on voting process approach. Section four explains the experimental activity we performed and section five describes the results. Conclusion and the future developments end the paper.

2 RELATED WORK

The study of the HVS behavior became relevant, in recent years, in the field of image and video elaboration and transmission research. It became a necessity when it was demonstrated that technical metrics are not strictly correlated with the user perceived quality (Wang, et al., 2004). These studies changed the focus of Image and Video Quality Evaluation techniques. The “device oriented” approach (Quality of Service – QoS), that ultimately brought to algorithms like the Peak Signal to Noise Ratio and the Mean Square Error, was left behind and replaced by a “user oriented” one (Quality of Experience – QoE) (Winkler & Mohandas, 2008). The foundation of the new model lies in the inclusion of subjective evaluation into algorithms and procedures that try to predict the level of satisfaction of the user, abandoning the focus on the technical parameters of the infrastructure. Today, finding an objective and robust link between the QoS and the QoE, is a challenging research topic, and can be very relevant to improve multimedia applications and services. The metrics that were developed after this conceptual shift are usually categorized as subjective or objective, while the previous type of categorization, as No Reference, Full Reference or Reduced Reference (NR, FR, and RR), still stands. This second differentiation depends on the necessity of the original multimedia content (not coded or elaborated in any way) in order to obtain results from the algorithm. The pros and cons of subjective and objective methodologies are discussed in (Kunze & Strohmeier, 2012) for subjective procedures and in (Le Meur, et al., 2010) for objective ones. To fill the gap between subjective and objective metrics, it is desirable to combine the precision in understanding the user perceived quality of subjective algorithms with the simplicity and fully automatic approach of objective algorithms. In (Zhu, et al., 2012), a new HVS methodology built on the retinal input is used to estimate the saliency of an image, while (Linying, et al., 2012) uses the current understanding of the HVS color space to propose a content-based image retrieval algorithm. These two studies, together with several others, show how taking into account the HVS features it is possible to enhance known and newly developed procedures (Lai, et al., 2013), obtaining more reliable results. The methodology is called “perceptual approach” to the QoE research topic. The key of this approach is to maximize the quality of the video or image regions that are deemed as most relevant by the users. In (Lee & Ebrahimi, 2012), the authors offer a deep and recent overview of how a perceptual approach to video compression has enhanced the efficiency of the known techniques. The main difference between our approach and the previously quoted ones is that we do not create a model of HVS (based on some physiological and/or psychological behavior), but we derived the response of HVS to visual stimuli directly from the experimental dataset provided by Eye tracking analysis. The choice has the advantage of considering the entire behavior of the HVS (not only the ones “coded” in the modelization). On the contrary, the main disadvantage is that a post-processing algorithm on the generated dataset is mandatory to provide reduced, manageable and meaningful data related to video saliency. Utilizing and exploiting the advantages of knowing how the HVS reacts and behaves to stimuli is called a “foveated approach” to IQA and VQA, and it is used to develop video or image saliency maps. The most accurate methodology to define these maps requires the utilization of an Eye Tracker device. Recording the point of gaze of the users on the stimuli returns real-world data, which means that it has to be considered as “irrefutable truth” to which all the modeling/evaluation methodologies should adhere. It is easy to understand how this methodology is useful to evaluate the effectiveness of objective quality evaluation algorithms, as the studies presented in Table 1 demonstrate. All the works presented in this table are good examples of how Gaze-Maps can be used as ground truth for IQA and VQA procedures and HVS modeling. In our VQA approach, we prefer to exclude the errors induced by the use of predictive algorithms; therefore, we apply our procedure on ground truth data. Our proposal is a new metric based on an innovative use of Eye-Tracked Gaze-Maps: each Gaze-Point of each map is weighted by all the other Gaze-Points on the same map, in pursuance of a self-definition of its relevance. Then, we perform a statistical analysis in search of eventual correspondence with the user perceived quality level. These maps identify the salient regions of the video stimuli we used in our experimental activity. The contribution in literature which is closer to our approach is

Table 1: Summary of Eye Tracking parameter used in Quality of Experience assessment activities.

Paper	N. of Tester	N. of Tester per group	N. of Original stimuli	Type of stimuli	N. of Total stimuli instances	Stimuli Duration	Stimuli Resolution	Impairment Techniques	ET frequency, accuracy
(Youlong, et al., 2012)	20	20	2	vid	24	10 s or more	1280x720	Compression	-
(Chamaret & Le Meur, 2008)	16	16	4	vid	4	-	720x480	Cropping	50 Hz, 0.5°
(Le Meur, et al., 2010)	36	36	10	vid	60	8 s	720x480	Compression	50 Hz, 0.5°
(Gulliver & Ghinea, 2009)	36	12	12	vid	12	10 s or more	640x480	Frame rate variation	25 Hz, -
(Hadizadeh, et al., 2012)	15	15	12	vid	12	5 to 10 s	352x288	Orignal	50 Hz, 1°
(Mittal, et al., 2011)	12	6	20	vid	60	30 s	720x480	Orignal (different tasks)	50 Hz, 1°
(Boulos, et al., 2009)	37	37	45	vid	100	8 to 10 s	1920x1080, 720x576	Cropping, resampling	50 Hz, 0.5°
(Albanesi & Amadeo, 2011)	18	6	19	vid	57	8 to 66 s	352x288	Compression	50 Hz, 1°
(Liu & Heynderickx, 2011)	40	20	29	img	29	10 s or more	768 x 512	Compression	50 Hz, 1°
(Engelke, et al., 2013)	15 to 21	15 to 21	29	img	29	10 to 15s	Varies	Varies	50 Hz, 1°
(Ninassi, et al., 2007)	20	20	10	img	120	pic 8s	512x512	Compression, blurring	50 Hz, 0.5°

(Mittal, et al., 2011), but in that case the activity is performed on still images. The authors studied the task dependency of the ocular behavior during an IQA procedure. However, even if the two approaches seem similar, our methodology differs because we considered relevant the position of the eye during saccades. To do that, we chose to cluster the samples during the whole view time of the users. Our Gaze-Points voting algorithm takes into account the time that occurs to HVS to "choose" which parts of the stimuli to stare at. This difference is fundamental to study our hypothesis. In case of the HVS gazing around a detail for some time without defining a fixation, excluding saccade times could cause information loss. We considered that interval of time relevant and indicative of the difficulty the HVS has in understanding the quality of the stimulus; therefore, we needed to know how the eye behaves in the period between fixations too. Even if previous works that state that the perceived quality is not precisely measureable by Eye Tracking devices exist (Ninassi, et al., 2007), (Le Meur, et al., 2010), the authors did not choose to eliminate all the possible influences on the viewers of their memory. Recent works demonstrate how knowing a content in advance is a huge bias that affects the visual strategy of a viewer (Laghari, et al., 2012), which then may lead to inconsistency of the retrieved data and of the conclusions. The choice of not excluding content repetition from visual experiments still makes sense, because it allows within-subject comparisons, but it is then impossible to define if results obtained are caused by the hypothesis under investigation, or if they are altered by the repetition of the content proposed to the testers. In order to exclude memory effect bias on the recorded data, we created a procedure that avoids any repetition of the same semantic content to the same user while performing the subjective Eye Tracking tests.

3 THE VOTING PROCESS ALGORITHM

The following steps compose the methodology for the Gaze-Map generation and analysis.

3.1 Dataset Creation

As we consider both time and space in our algorithm, it is necessary to know the sampling frequency of the Eye Tracking device. Each complete sample must include the timestamp of the moment it is recorded and the X and Y coordinates of the point of gaze on the screen for each eye. We decide to compress each original video using different bit rates, to create several quality-impaired instances of different instances of the same semantic video. The choice of the semantic content of the stimuli is relevant, too. It must be as general as possible, and the playlists for the experiment must be created to avoid any semantic repetition. Further explanations are presented in section 4, as we show how we gather the data for the experimental validation of the algorithm.

3.2 Initial Filtering

A first filtering operation is made to exclude any misreported record. The Eye-Tracking dataset usually includes negative spatial coordinates; those values mean that the gaze position at a given timestamp cannot be recorded, most probably due to minimal head movements of the observers that the device cannot compensate. Those records must be excluded.

3.3 Timestamp Normalization

The retrieved dataset usually cannot be studied "as is" because the samples usually are not perfectly aligned, due to experimental and/or the human behavior differences. Our decision of clustering the observation records over a fixed interval of time instead of comparing the full set of Gaze-Points (GP) retrieved by the experiments is instrumental in making irrelevant the impact of that kind of experimental error. The arrangement is also taken to have comparable sets of measures from different videos and observers. One important effect of this approach is to soften the impact of measure errors given by any head movement/inaccuracy of the instrument that could not be filtered in step 3.2. The idea behind this process is to reduce the set of data and to normalize it knowing the duration of each video. The chosen interval size is 1 s, which allows to group sequential records in number high enough to exclude the impact of accuracy measure errors. The shortest the interval, the more likely is to include altered records only. For example, when the tester's head is not perfectly motionless, the Eye-Tracker may empirically lose track of the gaze for dozens or even hundreds of milliseconds. We want an interval long enough to account for these possible errors. We call this phase clusterization, which generates clustered Gaze-Points (cGP). For example, a 30 s video (timestamp $t \in [t_0; t_l]$, where t_l is recoded on the last frame of the video) has 30 intervals, $i \in [1; i_d]$, with i_d=30. Tester one on video one must have only one clustered Gaze-Point record, cGP_i (X_{cGP_i}, Y_{cGP_i}) for each i, summarizing all the records of the raw dataset belonging to interval i. For i=1, all the Gaze-Points whose timestamp t was included between $t_{i-1}=t_0=0$ (the beginning of the recording of interval defined by i=1) and t_i=999 are included. The second Clustered Gaze-Point cGP_2 summarizes the records with $t \in [1000; 1999]$ and so on, until $i=i_d$ and $t \in [t_{l-1}; t_l]$. The average coordinates of all the records give each clustered Gaze-Point coordinates in the chosen interval. Therefore, cGP_i (X_{cGP_i}, Y_{cGP_i}) can be considered as the "center of gravity" of the subset of records it refers to, preserving the HVS behavior information carried by those records.
In (1), (2) ($X_{GP,t}$; $Y_{GP,t}$) are the recorded coordinates of X and Y of the raw dataset at time t.

$$X_{cGP,i} = \frac{\sum_{t=t_{i-1}}^{t_i} X_{GP,t}}{t_i - t_{i-1}}; \ i \in [1;\ i_d];\ t \in [t_0; t_l]; \qquad (1)$$

$$Y_{cGP,i} = \frac{\sum_{t=t_{i-1}}^{t_i} Y_{GP,t}}{t_i - t_{i-1}}; \ i \in [1;\ i_d];\ t \in [t_0; t_l]; \qquad (2)$$

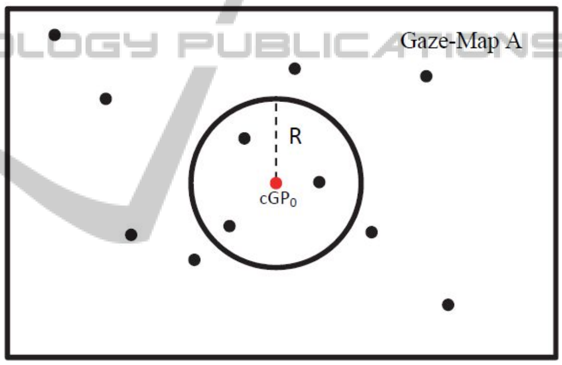


Figure 1: R-dependent analysis example, the weight of cGP_0 is 4.

3.4 Gaze-Map Generation

The next step is to create a Gaze-Map for each instance of each video. Each Gaze-Map is created by plotting all the cGP taken from the previous step. The number of Gaze-Maps created as result of this step is identical to the number of video instances involved in the Eye Tracking activity. Each map includes the data gathered from the whole set of observers that evaluate the stimulus.

3.5 R-Dependent Voting Process Analysis

This elaboration is repeated on all the Gaze-Maps. To simplify the exposition, let us consider a simplified Gaze-Map "A" (see Fig. 1). The goal is to make each cGP of A define its own weight, so the voting process is performed for each clustered Gaze-Point in the Gaze-Maps. The voting process depends on a parameter R, which is the radius of the circumference centered in the cGP under analysis (from Figure 1, cGP_0). The operation is fundamental because each cGP of A needs to be weighted by the cGP *in its neighborhood*, including itself. The voting process (similar to the one of the Generalized Hough Transform) is defined as follows: the weight of the current cGP_0 (X, Y) is voted by all the cGP on the same Gaze-Map (cGP_i(x, y)). The contribution to the weight of cGP_0 is 1 if cGP_i is included in the circumference of radius R, 0 otherwise, according to the following pseudo-code:

```
if ((x-X)-x)^2+((y-Y)-y)^2<=R^2 &&
Gaze-Map (x-X, y-Y)==1 {
c=c+1;} %weight counter
```

R is also the value chosen each time to perform a second filtering operation on the map border. It excludes an R-wide frame of pixels from the contribution to the weighting process. This feature aims to limit the importance of the difference between the video resolution and the monitor resolution. The problem is common when performing an Eye Tracking test on stimuli whose resolution is different from the one of the screen they are visualized on. With the variation of R, this filter is adaptive to the analysis we want to perform. After performing this step, each cGP of the Gaze-Map is associated to its *weight*. Obviously, the value of the weight depends of the proximity to other cGP and on the radius R. The statistical average is then computed, and an Average Clustered Gaze-Point Weight ($AGPW_{A,R}$) is generated for each value of R and each Gaze-Map.

3.6 Iteration Process

By performing the operations described in section 3.5 to the whole set of Gaze-Maps, the algorithm generates the mean value of $AGPW_{A,R}$ for each video. Finally, the values for each compression level are elaborated to obtain, given a known R, the average clustered Gaze-Point Weight for a given quality level (Quality Level Average Gaze-Point Weight – QLAGPW) and the standard deviation of clustered Gaze-Point Weights (Standard Deviation of QLAGPW – SDQLGPW) for each compression level used in the experiment. These two sets are the final, R-dependent, results of the procedure. And they are also the values at the basis of the ranking of video according the perceived quality, as explained in Section 5.

As the Average Clustered Gaze-Point Weight depends on R, we have generated a whole set of measures, for R varying from R1 (minimum, in pixels) to R2 (maximum, in pixels) with a fixed step, a, of 10 pixels. The choice of R depends on the video resolution and on the relative dimensions of objects on the scene; therefore we have considered a choice of R1 and R2 of $1a$ and $40a$, respectively.

The unit of R is pixels because, given the fact that the experimental set up is not changing for any observer or stimulus, the visual angle is not changing. Experimental results validate this choice (see section 4 and 5).

4 EXPERIMENTAL VALIDATION

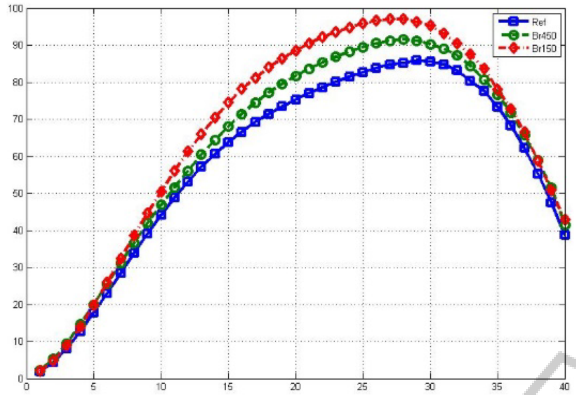
This section describes the experimental setup we adopted to validate our algorithm in a real-world environment.

4.1 Choice of Human Observers

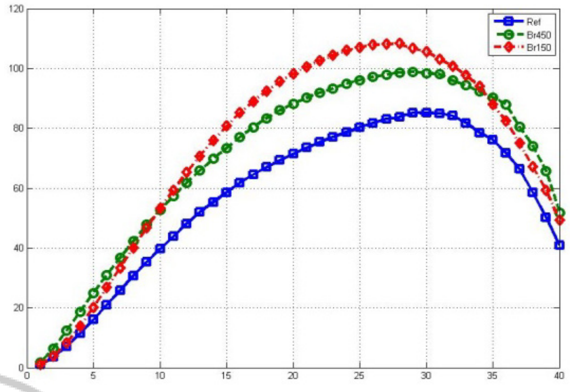
The number of testers involved in our study is 18, 10 males and 8 females, with an age varying from 22 to 27. All of them have normal or corrected-to-normal sight and participate for the first time to a QoE Eye Tracking test, even if they have regular experience in using computer interfaces to watch videos. All of them are graduate or undergraduate students who freely volunteer to participate to the activity. They are randomly divided into three groups of six testers. Six may seem an insufficient number of testers, but this choice has been successfully used in (Mittal, et al., 2011), with meaningful conclusions. We think that, rather than the number of testers for each playlist, the most important features of the experimental set up are the number of different semantics (videos) and the number of total impaired version (instances).

4.2 Media Selection

We use 19 different semantics taken by the current literature (Seeling & Reisslein, 2012), (University of Hannover, March 2011), (xiph.org, March 2011). The original files are YUV sequences, 4:2:0, in CIF resolution (352x288). For each of them (HQ) two impaired instances are created, bringing the total number of sequences to 57. The impaired copies are generated by compression. Each original video is compressed with the H.264/AVC algorithm at two different levels, altering the target bit-rate: 450 b/s and 150 b/s are the choices for medium and high



Graph 1: QLAGPW (y-axis) vs. varying radius of analysis (x-axis).



Graph 2: SDQLGPW (y-axis) vs. varying radius of analysis (x-axis).

compression (inducing medium and low quality – MQ and LQ) respectively. The aim was to create three different pools to build sufficiently varied perceived quality levels, similarly as in (Mittal, et al., 2011). The discussion of the effects of this choice as well as all the other details of the video dataset are deeply analyzed in (Albanesi & Amadeo, 2011).

4.3 Eye-tracking Protocol

The eye tracking dataset is gathered using a Tobii iViewX device, configured with Windows XP. It has a double CRT monitor setup, with the screen resolution and calibration and all the monitor settings as suggested by the user manual of the device itself. Explicitly, the monitor resolution and the recording field of the instrument were 1280x1024. This means that the video did not occupy completely the recording field so a black frame was added to create a neutral environment on the useless part of the screen. The sampling frequency of the Eye Tracking device is 50 Hz, and its accuracy is less than 1 degree of visual angle. All non-specified parameters of the activity comply with ITU-R BT 500-10 standard for Absolute Category Rating with Hidden Reference (ACR-HR) protocol. The choice of this protocol is due to its reliability, its ease of execution, and because it proved to be the most effective way to perform this kind of activity (Tominaga, et al., 2010). We used a group of questions directly asked to testers after each video to record the Mean Opinion Score on a five point discrete scale (Huynh-Thu, et al., 2011). We stated that stimuli were presented in a way to exclude any sort of memory effect: three playlists were created from the 57 instances in the starting pool (playlist A, B and C), and in each of them only one copy of the three at disposal for each video (Ref, Br450, Br150) was placed. If playlist A includes a stimulus compressed at 150 b/s, then it cannot include the same sequence compressed at 450 b/s or uncompressed. This means that each playlist has 19 videos and that the experiment duration is inferior to 30 minutes per tester, as advised by the guidelines. All the playlists includes six or seven videos for each compression level, to be as heterogeneous as possible. Playlists and testers groups are matched randomly in order to assign six viewers to each playlist.

5 RESULTS

In Graph 1, it is possible to see the regular pattern of Quality Level Average Gaze-Point Weight (QLAGPW) as a function of R. As easily predictable, the values of the average weight are increasing until the second filtering process (the R-wide frame of pixels excluded from voting, see section 3.5) becomes too extreme and begins to exclude relevant cGP from the voting process. We can identify an interval of R where the curve are completely monotonic *and* separated, from 10 to 27. The results show, for this interval, that the behavior related to the quality level becomes very regular: the higher QLAGPW, the lower the user perceived quality measured by the average MOS of the stimuli. In fact, the curves are ordered with the best video quality (*Ref* in the plot, blue line, avg. MOS 3.77, MOS variance 0.74) in the lowest position, the medium quality (*Br450*, green line, avg. MOS 2.81, variance 0.66) in the middle, and the lowest quality (*Br150*, red line, avg. MOS 1.86, variance 0.42) above. In addition to this first conclusion, Graph 2 shows that the SDQLGPW has the same regular behavior: the higher is the perceived quality; the lower is the Standard Deviation of the GP weight. The lower Weight of Gaze-Points means that points of gaze on the screen while watching the sequences are more distant from each other on high quality level stimuli, and the lower standard deviation in this case suggests that even if there was more space between fixations, those fixations were more regularly distributed on the screen than in other cases. In fact, a low Standard Deviation indicates that cGP weights are similar to each other. The most probable explanation is that the viewers had time and chance to gaze around the finest details in the case of high quality videos, and this lead to a more spread set of observations on the screen. It also means that in this case, each observation has an inferior but more similar number of near observations. The higher average weight and standard deviation of the data gathered from low quality videos, instead, suggest that the viewer focused on smaller portions of the screen, with a high density of "heavy" observations in it and a low number of "light" observations outside the region of interest. This confirms our initial hypothesis, which stated that a more impaired video is more challenging for the HVS, and therefore it is more difficult to understand the semantic meaning of a salient region. When the radius R of analysis becomes too high and, together with the filtering frame, starts to elide meaningful Gaze-Points or to consider too many of them as relevant, the curves start to decrease and the peculiar differences between the quality levels are lost. Therefore, the ranking has to be performed by considering only the portion of curves that are monotonic. Performing this procedure to groups of different compressed video offer the chance to rank them accordingly to their quality level, without knowing the performed compression parameters they were subject to. For this reason, we called our approach a No Reference metric.

The most relevant criticism that can be moved to our approach is that the HVS strategy is much more dependent on the semantic content of the chosen stimuli, rather than the perceived quality. This objection, that has its origin from several experimental activities like (Cerf, et al., 2009), can only be addressed by expanding the set of original stimuli to include heterogeneous semantic messages. Other works performed activities that involved two to twelve different subjects of stimuli (see Table 1), while our choice was to increase the number of sequences of our validation procedure to 19. The last step of the algorithm merges all the elaborated Gaze-Point at a given quality level into one single measure. This step includes all the measures on the same quality level making it as context-independent as possible. We could not increase the semantic dataset any more without making the experimental activity last for more than 30 minutes for each person involved. The guidelines show that the attention focus of testers rapidly decreases after that amount of time, and this could cause unreliability of the results. Another known problem is that users have different visual strategies when they are asked to perform different tasks on video, such as quality assessment, summarization or free viewing (Mittal, et al., 2011). Our paper addresses this issue by asking to all the observers involved to perform the same task (quality evaluation). This of course gives task-dependent results, but also allows excluding the presence of task bias between different samples because the whole set of data was obtained by involving the participants in the same quality assessment task.

6 CONCLUSIONS AND FUTURE DEVELOPMENTS

Our work is placed in the Multimedia Quality of Experience field of research. We propose a new algorithm to study the HVS behavior when subject to different quality level video under the hypothesis that a low quality video is more challenging for the HVS than a high quality one. Our approach is based on an Eye-Tracking experimental test. We proposed an algorithm that included a grouping phase of the data and a proximity analysis. Its core is the Gaze-Point weighting process, which returns a measure that is directly related to the distance of a Gaze-Point to the whole set of peers on the same map. The proposed algorithm, taking into account the distinct results gathered by the different testers, returns a score for each video that is the average weight of each Gaze-Point. We noticed that the proposed metric is inversely proportional to the user perceived quality, meaning that the HVS seems to act regularly. This behavior can be explained by our initial hypothesis: on high quality level stimuli the eye has more chances to gaze around the screen, while on low quality stimuli it is more difficult for the eye to understand the subject of the video, which leads to a more concentrated set of Gaze-Point, as the results of our experiments confirm.

The next step of our work will be to challenge this algorithm with different (not only lossy compression) quality impairment techniques (such as transmission-related ones) and different video resolutions, in order to expand the field of application of the algorithm, by considering other types of loss of quality and user experience devices (such as mobile devices).

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