IMAGE QUALITY AND VISUAL ATTENTION INTERACTIONS: TOWARDS A MORE RELIABLE ANALYSIS IN THE SALIENCY SPACE

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ABSTRACT

Understanding bottom-up and top-down visual attention mechanisms related to visual quality perception can be greatly beneficial for the design of effective objective quality metrics. Subjective studies based on eye-movement tracking have been recently published that try to get more insight in these interactions. However, it is still not easy to find coherence across their results, also due to the different methodologies adopted to analyze eye-tracking data. In this paper we propose a robust methodology to measure differences between eye-tracking data collected under different experimental conditions. The proposed method takes into account inter-observer variability and content effects, producing results that give an accurate insight in attention variations.

***Index Terms*—** Visual quality perception, Visual attention, Saliency, Eye-tracking.

1. INTRODUCTION

Within the factors that contribute to the quality of multimedia experience, perceived visual quality is of major importance. Researchers have tried to understand human visual quality preferences for a long time now, achieving some remarkable results [1], yet without a full understanding of the mechanisms lying behind it.

One of the latest tendencies in visual quality perception is the study of visual attention (VA) related to quality preferences. While we observe a scene, our collection of information is actively limited and controlled through oculomotor mechanisms. These mechanisms allow the gaze of attention to hold on a particular location (fixation) or to shift to a preferred location when sufficient information has been collected from the current one (saccades). Fixations are instinctively concentrated on highly informative areas; as a consequence, the amount of data to be further processed by the brain is minimized, yet maximizing the quantity of useful information. In a first stage of the observation the selection of fixation locations is fully driven by the intrinsic visual properties of the scene (bottom-up attention). As proposed by Koch and Ullman [2], every location in an image can be characterized by a value indicating its "attractiveness" for the human eye. This indicator is also known as saliency.

It has been hypothesized that visual distortions appearing in less salient areas might be less visible and thus concur to the final quality judgment to a minor extent. A confirmation of this hypothesis might severely impact the design of image enhancement algorithms and their related objective visual quality metrics in particular. However, these metrics target the reproduction of perceived quality scores, which can only be obtained during an evaluation task. It is well-known that VA is not only influenced by bottom-up characteristics in the observed scene, but also by so-called top-down mechanisms, which are volition controlled and drive the eye movements according to the task that the viewer performs [3,4]. Therefore, the question whether the quality judgment task may have an impact on deviations in eye-movements from natural scene saliency is recently raised. As a result, a number of studies that investigate bottom-up and top-down mechanisms in the interaction between image quality and visual attention are lately published [5-10].

Dealing with still images, Alers et al. showed how JPEG artifacts in the background influenced the final quality judgment to a lesser extent as compared to artifacts located in highly salient areas [5]. The pioneering work by Vuori and others [6] showed that different quality evaluation tasks and to some extent the quality of the judged image had an impact on the saccades' duration. Ninassi et al. [7] proved that eye-tracking data collected during quality evaluation deviated from those recorded under free viewing by comparing the obtained saliency maps and fixation durations. Their results were confirmed in the study by Vu et al. [8], who identified an influence of the kind of distortion on the location of the fixations while scoring, though without quantifying it. Conversely, the study in [9] proved in a quantitative way how the kind of distortion did not influence attentive paths in a strong way, while the quality of the judged picture did. Le Meur et al. found in [10] that the quality evaluation task had a more limited impact in the video domain than in the image domain. Although all these studies provide some knowledge on interactions of quality perception and visual attention, it is still not easy to arrange the results in a uniform theory. This

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is partly due to the different methodologies adopted to analyze eye tracking data; some studies focus on the analysis of the eye-movements, while others analyze the deduced saliency.

The aim of this paper is to propose a unified framework to robustly measure saliency similarity, based on the concept of prediction efficiency first introduced in [11]. Such framework is shown to give good insights in saliency deviations, yet being robust to inter-observer variability.

The remainder of this paper is organized as follows. Section 2 provides an overview of the methodologies to analyze eye-tracking data. Section 3 introduces the notions of upper empirical similarity limit and of efficiency. Section 4 applies the concept of efficiency to measure the differences in saliency between databases [12] and [13]. Finally, conclusions are drawn in section 5.

2. EYE TRACKING DATA ANALYSIS

The majority of the studies on interactions between visual attention and visual quality perception is nowadays based on tracking eye-movements. In a typical experiment, eye movements of a number of observers are first recorded for different images in a reference (control) setting, e.g., during task-free image observation. Then, one or more independent variables are introduced in the experiment, and the eye movements are recorded again with the new setup. Examples of independent variables can be the task given to the observer (e.g. quality scoring or element counting), the manipulation of the image quality level or a combination of the above.

Eye-trackers typically output a collection of fixation points and saccades, which need to be further processed to provide insight in the actual visual attention profile. Therefore, assuming for simplicity that the experiment is performed to observe the effect on visual attention of a single independent variable *IV*, for every image *I* in the dataset a collection of eye movements $\mu_R^{(I)}$ is obtained under the reference condition, and the collection $\mu_{IV}^{(I)}$ is obtained under the test condition, i.e. including the effect of the independent variable. In literature two main groups of approaches can be identified for the analysis of eye-tracking data, depending on the domain in which the analysis is performed.

A first group of approaches studies differences in some characteristics of the eye-movements, such as the duration and frequency of fixations [7], or the velocity, duration and amplitude of the saccades [14]. Eye movement properties are measured across $\mu_R^{(I)}$ and $\mu_{IV}^{(I)}$ and compared to determine whether the introduction of the independent variable has an effect on visual attention. In [6] a consistent decrease of duration between saccades recorded during a quality evaluation task and saccades recorded during a counting task is shown. In [7], however, the analysis of fixations' duration does not reveal relevant differences between free looking of high quality images and a scoring of quality of impaired images. The authors themselves prove later in their paper that this result is only partial and that quality evaluation actually affects attentional mechanisms. Eye-tracking data analysis based on eye movements only is in this sense limited, referring mainly to the temporal aspect of the observation, but lacking in spatial scope.

The second group of approaches transfers the eye-movement data into saliency maps. These maps [2] are a visual representation of the probability that a location of the scene is attended by the average observer. In this sense, both spatial and temporal information can be transferred to a saliency map. Given K collections of eye movements $\mu^{(I,k)}$, k = 1,…, K , each corresponding to a different observer k, the following procedure can be applied:

1. Extract the set of fixation locations on the image $\mathbf{F}^{(I,k)}=[(x_1,y_1), (x_2,y_2), \ldots, (x_n,y_n)]$, where n is the number of fixations included in $\mu^{(I,k)}$
2. Extract from $\mu^{(I,k)}$ the duration of each fixation $\mathbf{D}^{(I,k)}=[d_1, d_2, \ldots, d_n]$
3. Create the fixation map
$$FM^{(I,k)}(x,y)=\begin{cases} d_i & if \quad (x,y)=(x_i,y_i)\in \mathbf{F}^{(I,k)} \\ 0 & otherwise \end{cases}$$
4. Create an average fixation map over all observers
$$FM^{(I)}(x,y)=\frac{1}{K}\sum_{k=1}^{K} FM^{(I,k)}(x,y)$$
5. Apply a Gaussian patch having a standard deviation σ of the amplitude of the fovea (about 2º of visual angle) to each fixation point in $FM^{(I)}(x,y)$ to obtain the saliency map, $SS^{(I)}(k,l)$:
$$SS^{(I)}(k,l)=\sum_{j=1}^{T}\exp[-\frac{(x_j-k)^2+(y_j-l)^2}{\sigma^2}],$$
where T is the total number of fixations over all observers.

Each element of $SS^{(I)}$ expresses the probability that the average observer attends location (k,l) over the observation period. Thus, given two saliency maps $SM_R^{(I)}(x,y)$ and $SM_{IV}^{(I)}(x,y)$, the impact of the independent variable on visual attention can be assessed by evaluating differences among the two distributions.

Even without including temporal information (i.e. selecting $\mathbf{D}$ = $\mathbf{1}$) an analysis based on saliency maps can bring significant results in the comparison between a test and reference condition, as in [7]. However, the approaches within this group are fragmented and use very different metrics to establish differences among saliency maps. Therefore, there comparability across results is often limited.

3. ANALYSIS OF SALIENCY

3.1. Measures of similarity between saliency maps

Many methods have been proposed to compare saliency maps, not always bringing consistent information. The main differences between these methods lay in the interpretation of the nature of the saliency information (probability distribution, matrix) and in the target of the measure (e.g., similarity or divergence). In the following we describe four of the most popular measures and try to point out common traits and differences between them. Furthermore, we introduce a fifth similarity measure, i.e. the structural similarity index (SSIM) [1].

The simplest measure of similarity for saliency maps is perhaps the Linear Correlation Coefficient (LCC), which quantifies the (symmetrical) strength of the linear relationship between two distributions. Given two saliency maps $SM_R^{(I)}$ and $SM_{IV}^{(I)}$, LCC ranges between [-1, 1]:

$$LCC(SM_R^{(I)}, SM_{IV}^{(I)}) = \frac{\operatorname{cov}\left(SM_R^{(I)}, SM_{IV}^{(I)}\right)}{\sigma_R \sigma_{IV}}$$

A value of LCC = 1 indicates identical maps, while LCC = 0 indicates uncorrelated maps. Negative values of LCC indicate inversely correlated maps (i.e, the two maps are complimentary to 1).

The Kullback-Leibler divergence (KLD) gives instead a measure for the dissimilarity between a test distribution and a reference one. As such, it is a positive quantity; it increases with the dissimilarity in the distributions, and KLD = 0 only in case of identical distributions. The deviation of $SM_{IV}^{(I)}$ from $SM_R^{(I)}$ is computed as:

$$KLD\left(SM_R^{(I)}, SM_{IV}^{(I)}\right) = \sum_{x,y} SM_{IV}^{(I)}(x,y) \log\left(\frac{SM_{IV}^{(I)}(x,y)}{SM_R^{(I)}(x,y)}\right)$$

The Area Under Curve (AUC) is another indicator of similarity between saliency maps. It has been widely used in literature to evaluate the performance of visual attention models [11]. This indicator measures the area under the Response Operation Characteristic, that is in turn derived from the number of elements coherently labeled as salient in $SM_{IV}^{(I)}$ and $SM_R^{(I)}$ versus the number of elements labeled as salient in $SM_{IV}^{(I)}$ and which are not salient in $SM_R^{(I)}$. A value of AUC = 1 indicates perfect match between the maps, AUC = 0.5 indicates chance match.

A fourth measure first proposed to evaluate VA models [15] and recently adopted in subjective studies is the Normalized Scanpath Saliency (NSS). In this case, $SM_{IV}^{(I)}$ is normalized to have zero mean and then compared to $FM_R^{(I)}$. For every fixation in $FM_R^{(I)}$, the value of $SM_{IV}^{(I)}$ at the same location is measured; the average of these measurements gives an indication of how similar the maps are. NSS = 0 implies no similarity. Higher values of NSS indicate higher similarity among maps.

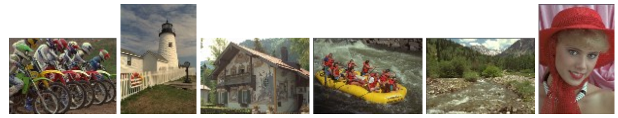

Figure 1. Images involved in the study. From left to right: Bikes, Light House, Painted House, Rapids, Stream and Woman Hat.

A fifth way to inspect similarities between saliency maps is to look for structural coherence between these maps. In this sense, saliency maps can be considered as images, and their structure can be compared through the well-known Structural Similarity Index (SSIM) [1]. Originally designed to measure differences in quality between an original and an impaired image, the SSIM can also be used to calculate how much the structure of $SM_{IV}^{(I)}$ has changed with respect to the reference $SM_R^{(I)}$:

$$SSIM(SM_R^{(I)}, SM_{IV}^{(I)}) = \frac{\left(2\mu_R \mu_{IV} + c_1\right)\left(2\sigma_R \sigma_{IV} + c_2\right)}{\left(\mu_R^2 + \mu_{IV}^2 + c_1\right)\left(\sigma_R^2 + \sigma_{IV}^2 + c_2\right)}$$

SSIM = 1 indicates that the saliency maps have exactly the same structure; the closer the SSIM value is to 0, the less similar is the structure between the two saliency maps.

3.2. Upper empirical similarity limit and efficiency

As pointed out by Stankiewicz et al. [11], eye tracking data, and therefore saliency, are subject to a high inter-observer variability. In other words, if we ask two groups of people to observe the same image with the same experimental setup, the two resulting saliency maps will deviate from each other to some extent. Using one of the similarity measures introduced in the previous section, one might find a deviation and ascribe it to the independent variable effect, while actually the dissimilarity may be due to inter-observer variability only. Therefore, to fairly evaluate the impact of an independent variable on saliency, we need to establish a similarity upper bound taking into account inter-observer variability.

To do that, we build on Stankievicz et al.'s notion of upper-theoretical performance limit for predicting eye-fixations [11]. We define the Upper Empirical Similarity Limit (UESL) for saliency as the maximum achievable similarity between the saliency maps derived from two different (groups of) humans under the same experimental conditions. The measure of similarity depends on the metric adopted to compare the saliency maps, and can be selected among those presented in section 3.1.

For each image I observed in the reference condition observers are divided into two equally sized groups K_1 and K_2, and the corresponding $SM_R^{(I,K1)}$ and $SM_R^{(I,K2)}$ are calculated. The upper empirical similarity limit is computed as:

$$\text{UESL} = S\left(SM_R^{(I,K1)}, SM_R^{(I,K2)}\right),$$

where S is a generic measure of saliency similarity and S $\in$ {LCC, AUC, NSS, SSIM}. The effect of the independent variable on visual attention can now be defined by the test efficiency, being the similarity between the saliency maps obtained in the test and reference condition versus the UESL:

$$E = S\,(SM_{IV}^{(I)}, SM_{R}^{(I)}) \,/\, \text{UESL}.$$

It should be noticed that for the KLD defining an upper bound is not meaningful, as high KLD values correspond to bigger dissimilarities between maps. Therefore, for the KLD we define a Lower Empirical Divergence Limit (LEDL) and the consequent test efficiency as:

$$\text{LEDL} = \text{KLD}\,(SM_{R}^{(I,K1)}, SM_{R}^{(I,K2)});$$

$$E = \text{LEDL} \,/\, \text{KLD}(SM_{IV}^{(I)}, SM_{R}^{(I)}).$$

The test efficiency E gives eventually a measure of the similarity between saliency maps obtained in different experimental conditions, and also takes into account inter-observer variability. Lower values of E indicate lower similarity between maps. It should be noted also that the limits are being defined empirically, and therefore, they cannot be considered as hard limits. As a consequence, E can exceed 1.

4. STUDYING VISUAL ATTENTION DEVIATION IN QUALITY SCORING THROUGH EFFICIENCY

In this section we exploit the notion of efficiency to investigate to what extent saliency deviates as a consequence of a scoring task. In particular, we look for the effect of two independent variables: the kind of distortion and the quality level of the observed image. This study, based on existing eye-tracking datasets [12, 13], has a twofold goal: first, to validate existing knowledge with the newly defined efficiency paradigm, and second, to compare similarity measures in order to narrow the range of metrics useful to detect changes in saliency.

4.1. Eye-tracking data

The dataset of the TUD Interactions Eye-tracking database (TUD-IE) [12] includes eye-tracking data recorded during the quality scoring of 54 impaired images derived from 6 original contents (*C*) extracted from the LIVE database [16] (see Figure 1). The dataset allows analyzing the effect of quality assessment on the deviation in saliency due to the kind of distortion applied (first independent variable) or to the quality level of the image (second independent variable). We will refer in the following to this collection of data as μ_{TI}. Three kinds of distortions (*d*) are considered: JPEG compression, White Noise and Gaussian Blur. For every content *C* and distortion, three images are selected from the LIVE database according to their quality level (*q*): a highly distorted one, one with a medium distortion level, and one for which the applied distortion just slightly compromises the quality. The eventual image set contains for each image content 9 distorted versions:

$$\mathbf{I}_{TI} = I_{d,q}^{C} \quad d \in \{\text{Blur,Jpeg,Noise}\} \quad q \in \{\text{Low,Medium,High}\}$$
$$C \in \{\text{Bikes,Lighthouse,Paintedhouse,Rapids,Stream,Womanhat}\}$$

Experiments were carried out using a non-intrusive eye tracker on 14 subjects.

As reference data, we use the TUD LIVE eye tracking database [13] (μ_{FL}). Eye movements were recorded while 18 subjects observed the 29 source images of the LIVE database [11] under similar environmental conditions and with similar equipment as for the TUD-IE database. Participants freely looked at the images for 6s. From this TUD-LIVE dataset we include in our analysis only the data related to the six contents included also in the TUD-IE dataset. Saliency maps were obtained from μ_{FL} and μ_{TI} by applying the procedure described in sec. 2 and using **D = 1.**

4.2. Empirical similarity limit computation

The Upper (Lower) Empirical Similarity (Divergence) limit was computed for each of the six contents in figure 1 and for each of the similarity measures described in section 3.1. The procedure proposed in section 3.2 was applied 50 times and the average of the resulting values was taken as a robust estimator of UESL (LEDL). To compute the AUC, the approach adopted in [9] was followed. A threshold equivalent to the contribution in saliency of 2 observers was chosen, i.e. a saliency level higher than 54. Figure 2 reports the values obtained for each content and similarity measure.

For the three measures that vary within a known range (LCC, SSIM and AUC) the values significantly depart from 1 (perfect similarity). This result points out how important it is to take into account inter-observer variability when analyzing saliency data. Indeed, a LCC between two maps equal to 0.8 is often considered sufficiently low to claim an effect of the independent variable, but in fact could be simply due to disagreement among observers. It is also interesting to notice how the LCC and AUC well capture the typical higher inter-observer agreement when the image has a clear region of interest (e.g. Woman_Hat or Rapids).
The KLD and the NSS seem to be most sensitive to image content differences, while the SSIM is the similarity measure that varies over the smallest range with image content. It should be noted that lower variability with respect to image content is desirable. To determine the extent of the effect of independent variable on visual attention, similarity between SM_{IV} and SM_R is usually analyzed across contents (typically, averaged). In this scenario, a similarity measure with a high sensitivity to

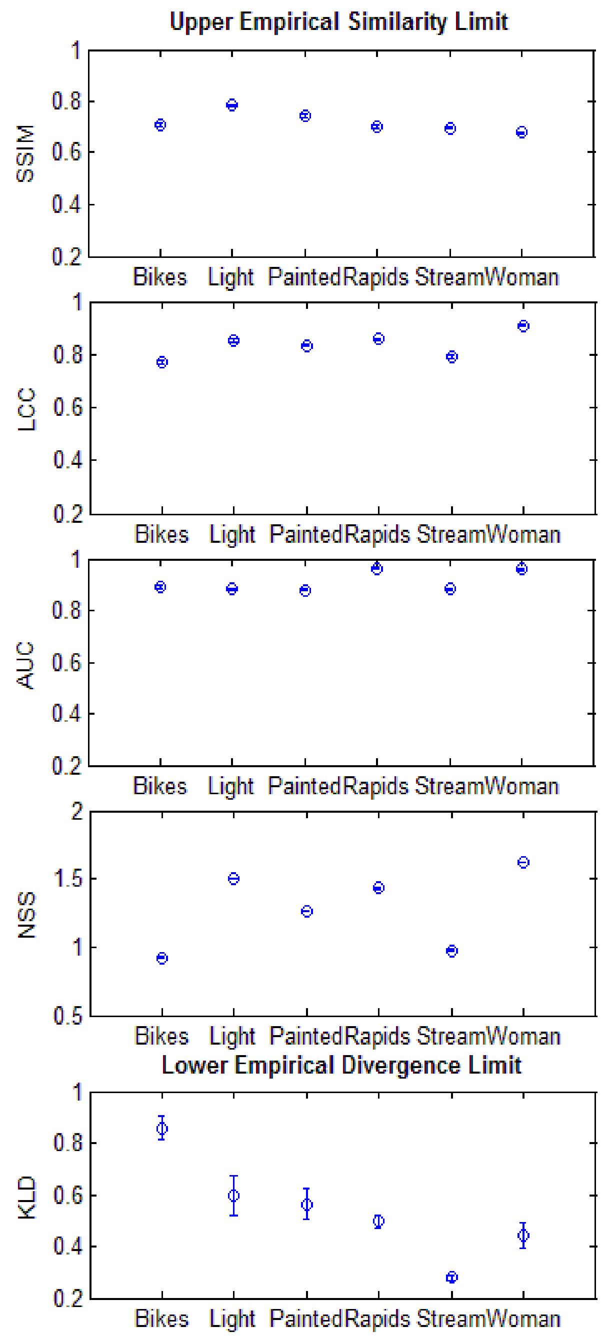

Figure 2 – Upper empirical similarity limit for the LCC, SSIM, AUC and NSS metrics, and Lower Empirical Divergence Meeting for KLD. The values are reported for each image considered in the study and originally drawn from LIVE [16]

image content could introduce noise in the analysis, thus decreasing the chances of correctly detecting the effect of the independent variable. Furthermore, the KLD presents high variability across the 50 trials adopted for the UESL computation. This might indicate a high sensitivity to inter-observer differences as well.

4.3. Detecting the impact of quality level and distortion type on visual attention using efficiency

To further reduce the effect of content variability on our analysis, we compute efficiency content-wise. Thus, for every image $I^C_{d,q}$ in μ_{TI} and the corresponding content I^C in μ_{FL} we compute:

$$E^C_{q,d} = S\,(SM^C_{TI,q,d}, SM^C_{FL}) \,/\, \mathrm{UESL}(SM^C_{FL})$$

To inspect the effect of quality level on visual attention, we average the values $E^C_{q,d}$ over content and distortion type:

$$E_q = \frac{1}{18}\sum_{d,C} E^C_{q,d} \qquad q \in \{low, medium, high\}$$

The resulting values for each of the considered similarity measures are shown in figure 3. The same procedure is applied to investigate the effect of distortion type, by averaging the efficiency values over content and quality level:

$$E_d = \frac{1}{18}\sum_{q,C} E^C_{q,d} \qquad d \in \{blur, jpeg, noise\}$$

Results for all the metrics are compared in figure 4.

It can be immediately noticed that in both cases, the efficiency based on AUC has, on average, a value above 1. This implies that saliency measured under scoring is more similar to free-looking saliency than saliency compared between different groups of observers. An explanation for this might be that UESL is computed on maps that account for fewer observers (half of the participants) and thus are less stable. However, the AUC trend contradicts a solid record of results in literature [5-8] and the results obtained with the other saliency measures in this study. Thus, the AUC might be a less reliable similarity measure when embedded in the efficiency framework The SSIM-based efficiency measure reveals an effect of the quality level on visual attention. In particular, the structure of scoring saliency seems to depart more from the structure of free-looking saliency when the quality decreases. This effect is also detected by the KLD, but not by LCC and NSS. None of the metrics instead detects an effect of the distortion type on saliency, in line with the results already presented in [8].

5. CONCLUSIONS

A framework was proposed to analyze differences in saliency maps measured under different experimental conditions. The framework is robust against interobserver variability and robust across content differences. Four of the most popular saliency similarity measures (LCC, KLD, AUC and NSS) were embedded in the framework and their

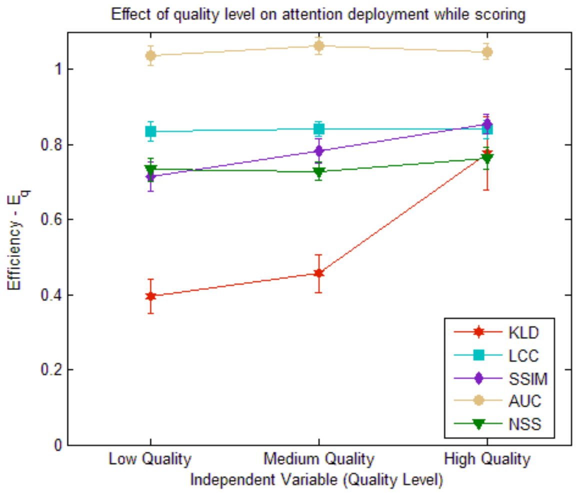

Figure 3 – Effect of the quality level on attention deployment while scoring measured through different implementations of efficiency. Efficiency measures based on different similarity measures provide quite different results, however, the effect of quality on visual attention deployment while scoring can be detected.

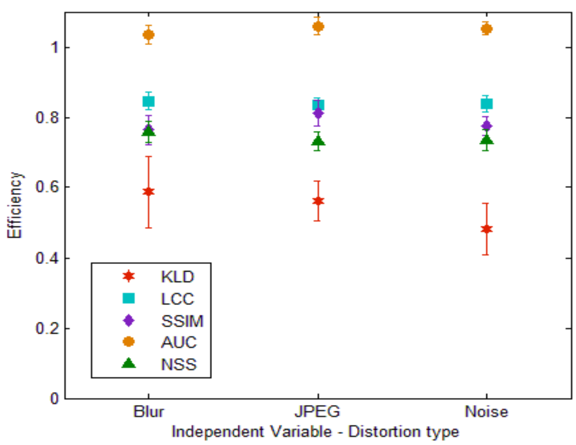

Figure 4 – Effect of the distortion type on attention deployment while scoring measured through different implementations of efficiency. Efficiency measures based on different similarity measures provide quite different results, but in general no effect of distortion type on visual attention deployment while scoring can be detected.

output compared. The structural similarity index (SSIM) was also proposed as a measure of saliency similarity.

Each of the considered measures was shown to be sensitive to changes in content and saliency in a different way. As a consequence, to obtain a clear overview of differences in attention deployment, it is advisable to apply the efficiency framework for at least two of these measures. In particular, the SSIM, LCC and AUC are conveniently less sensitive to the image content. Our experiments show that the AUC might not reliably represent differences in saliency between a reference and a test experimental condition. The SSIM seems instead to be a good candidate measure, being insensitive to content changes but able to detect differences in saliency. Finally, the KLD can carry important information regarding changes in saliency, although it is also very content dependent.

REFERENCES

[1] Z. Wang and A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli, "Image quality assessment: From error visibility to structural similarity," IEEE Trans. Image Proc., Vol. 13, no. 4, 2004.

[1] C. Koch and S. Ullman, “Shifts in Selection in Visual Attention: Toward the Underlying Neural Circuitry,” Human Neurobiology, vol. 4, no. 4, pp. 219-27, 1985

[2] Yarbus, “Eye movements and vision,” New York: Plenum Press, 1967.

[3] R. Desimone and J. Duncan, “Neural mechanisms of selective visual attention,” Annual Review of Neuroscience, 18, 193–222, 1995.

[4] H. Alers, H. Liu, J.A. Redi and I. Heynderickx “Studying the risks of optimizing the image quality in saliency regions at the expense of background content,” in proc. IS&T/SPIE Electronic Imaging - Image Quality and System Performance VII, 2010

[5] Vuori, T., Olkkonen, M., Pölönen, M., Siren, A., and Häkkinen, J. Can eye movements be quantitatively applied to image quality studies? In Proceedings NordiCHI 2004. ACM Press, New York, NY, 2004, 335-338

[6] Ninassi, O. Le Meur, P. L. Callet, D. Barba, and A. Tirel, “Task impact on the visual attention in subjective image quality assessment,” Proc. EUSIPCO-06, 2006.

[7] Vu, T., Larson, E. C., and Chandler, D. M., “Visual Fixation Patterns when Judging Image Quality: Effects of Distortion Type, Amount, and Subject Experience,” Proc. IEEE SSIAI 2008, 73-76 , 2008.

[8] Redi JA, Liu H, Zunino R, Heynderickx I. “Interactions of visual attention and quality perception”, In: IS&T/SPIE Electronic Imaging 2011 and Human Vision and Electronic Imaging XVI. Vol 7865. 2011.

[9] Le Meur, A. Ninassi, P. Le Callet and D. Barba “Do video coding impairments disturb the visual attention deployment?”, Elsevier, Signal Processing: Image Communication, vol. 25, Issue 8, pp. 597-609, September 2010.

[10] J. Stankiewicz, N. J. Anderson, R. J. Moore” Using Performance Efficiency for Testing and Optimization of Visual Attention Models”, in In: IS&T/SPIE Electronic Imaging 2011 and Human Vision and Electronic Imaging XVI. Vol 7865. 2011

[11] TUD Interactions eye-tracking database, available at: http://mmi.tudelft.nl/iqlab/eye_tracking_3.html

[12] TUD LIVE eye-tracking database, available at: http://mmi.tudelft.nl/iqlab/eye_tracking_1.html

[13] Q. Huynh-Thu and L. Schiatti “Examination of 3D visual attention in stereoscopic video content”, in IS&T/SPIE Electronic imaging 2011 - Human Vision and Electronic Imaging XVI, Vol. 7865

[14] R. J. Peters, A. Iyer, L. Itti, and C. Koch, “Components of bottom-up gaze allocation in natural images,” *Vision Research*, vol. 45, no. 18, pp. 2397–2416, August 2005.

[15] Sheikh, R., Wang, Z., Cormack, L., and Bovik, A., “LIVE Image Quality Assessment Database,” http://live.ece.utexas.edu/research/quality, 2007