Subjective matters: from image quality to image psychology

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ABSTRACT

From the advent of digital imaging through several decades of studies, the human vision research community systematically focused on perceived image quality and digital artifacts due to resolution, compression, gamma, dynamic range, capture and reproduction noise, blur, etc., to help overcome existing technological challenges and shortcomings. Technological advances made digital images and digital multimedia nearly flawless in quality, and ubiquitous and pervasive in usage, provide us with the exciting but at the same time demanding possibility to turn to the domain of human experience including higher psychological functions, such as cognition, emotion, awareness, social interaction, consciousness and Self. In this paper we will outline the evolution of human centered multidisciplinary studies related to imaging and propose steps and potential foci of future research.

Keywords: image quality, image psychology, individual differences, image content, subjectivity

1. INTRODUCTION

Image quality has been one of the major topics of the Human Vision and Electronic Imaging (HVEI) conference throughout the 25 years of its existence. It has even become a tradition to dedicate one day of this yearly event to image quality with typical sessions such as Early Vision Image Quality and Higher-Level issues in Image Quality. This does not mean that there was no interest in image quality before 1988. In an extensive historical overview Chandler¹ pointed out that since the end of the 1920's image quality has systematically been investigated in relation to evaluating optical systems and analog television broadcast and display systems. In the 1950's, for example, engineers at British Telecom already started to look into the relation between perceived image quality and the corresponding degradation or impairment, the way multiple degradations combine into an overall quality judgment and the development of appropriate subjective evaluation methods. This resulted in J.W. Allnatt's "Law of Subjective Addition"² stating that impairment is inversely proportional to image quality and that distinct impairments add up when they occur simultaneously. He also introduced the well-known 5-point grading scales, ranging from "bad" to "excellent" and "very annoying" to "imperceptible" for assessing image quality and impairment respectively³, that can still be found in Recommendation ITU-R BT-500 "Methodology for the Subjective Assessment of the Quality of Television Pictures"⁴. Later on, the relation between image quality and impairment was found to be linear, while Minkowski metrics proved to be a better way of combining simultaneously occurring impairments into one overall impairment score^{5,6}. An interesting observation from studies like this one was that there are no fundamental differences in image quality assessment for analog and digital image material.

In 1987, Watson⁷ made an important distinction between perceptually lossless and perceptually lossy image coding, thus acknowledging the relevance of understanding and modelling the impact of coding artifacts on perceived image quality. Research into image integrity⁸ or artifactual quality⁹, referring to the relation between coding artifacts and image preference, became an important focus of the HVEI conference, in particular in the first years of the conference¹⁰ (but see Chandler¹ for a continuous interest in this topic). The approach consisted of incorporating low-level human visual system (HVS) models into image quality metrics. This was inspired by the idea that the human

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visual system has remained constant over time, that is, "...Although personal preferences can and do change over time and do vary from person to person, the underlying neural circuitry and biological processing strategies have changed little over measurable human history..."¹. It was therefore hoped that such HVS-based models could accurately predict and describe perceived

image quality. Unfortunately, even at threshold level this turned out not to be true as was nicely illustrated in an experiment on error visibility for stills taken from compressed video material¹¹. The results of this experiment clearly showed that non-experts are less sensitive to the "…very small and localized…" artifacts (block-structures, quantization noise and blur) than the experts but also that experts with detailed knowledge of the algorithm employed were slightly more sensitive than experts without this knowledge. But the really interesting observation was that the expert who had taken part in the development of the algorithm was only more sensitive to the coding errors in the two images that were used to develop the algorithm. For the other image, unknown to him, "…his lack of advance knowledge led to more or less random results…"¹¹. Apparently, the well-informed experts knew exactly where to look for the artifacts, a finding that cannot be accommodated by most of the low-level HVS-based models.

Although the focus in image quality research on quantifying and eliminating distortions and artifacts caused by capture, transmission, compression and reproduction employed in modern imaging systems benefitted a wide variety of applications, and has become "an active subdiscipline of image processing"¹, a different line of inquiry has been emerging in recent years, inspired by observations of individual preferences, the role of scene content and higher level cognitive processes involved in evaluating image quality.

This paper presents a brief overview of the research trends that developed in the context of image quality evaluation and are reflected in the publications of the HVEI conference and elsewhere. These trends point toward image psychology as a nascent field of investigation, where the emphasis is on the full spectrum of human reactions to images and media rather than on the assessment of image quality and visibility of distortions. As we will show, in this line of research the primary focus shifts from the image, to the user.

2. IMAGE QUALITY: BROADENING OF SCOPE

2.1. From fidelity to enhancement

As mentioned earlier, to address artifacts involved in capture, compression, transmission and reproduction of images in electronic imaging systems, low-level HVS models were developed and incorporated into image quality metrics^{12,13,14,15,16,17}. The aim was to evaluate and predict the visibility of distortions introduced within an image processing chain in comparison to the original undistorted image. This approach was constrained by the characteristics of the baseline original image, often implicitly assumed to be an artifact-free optimum. This assumption effectively led to equating image quality and image fidelity. However, as Silverstien and Farrell have shown for images with halftone textures¹⁸, there was only a moderate correlation between image fidelity and image quality. Moreover, the earlier studies on color reproduction of film-based photographic images provided the evidence that colorimetrically accurate reproduction of natural scenes does not necessarily ensure the highest image quality results. On contrary, systematic distortions for certain object colors (the colors of skin, sky and grass) were preferred^{19,20,21,22}. These effects were shown to relate to memory (memory colors) and were culture dependent. As an example, the preference for the color of skin was close to the mean memory color for Caucasian flesh (x, y) = (0.3548, y)0.3441) under Illuminant C, while being significantly different from the natural Caucasian flesh color under the same illuminant $(x,y) = (0.3786, 0.3463)^{19}$. These and other related experimental investigations published in the 1950s-1980s, seemed to be among the first ones to consider higher level psychological functions for image quality^{\dagger}. They also indicated the possibility of achieving a superior image quality, beyond a "true" reproduction.

Further studies of color variations of digital images in perceptually uniform color spaces and their effects on global perceptual attributes and image quality have shown that indeed, a reliable enhancement of image quality can be produced by selectively increasing chroma or saturation values of image pixels and thereby increasing image colorfulness^{24,25,26,27,28}. The upper limit of a colorfulness increase still having a positive impact on image quality

[†] For additional early references on the role of memory for object color preferences see ²³.

was constrained by the apparent naturalness, which was thought to reflect the knowledge of real world scenes stored in memory^{24,25,26,27,28,29}. The aforementioned studies effectively demonstrated that there exist types of image manipulation that reflects conditions and corresponding perceptual and cognitive processes occurring in every day human experience: in all scenes except a highly saturated professionally photographed portrait^{24,25}, a measured increase in colorfulness accompanied both, higher quality and naturalness ratings.

2.2. The role of visual attention

In trying to improve models of image quality, researchers turned to the concept of the region of interest (ROI): an image area that has a relatively larger weight compared to other local areas when different treatments of various local areas are considered³⁰ and when different distortions in the image are summated in an image quality metric^{31,32,33}. This led to focusing on saliency maps and the role of selective visual attention in defining ROI using data from image analysis and visual attention modeling^{34,35}, and consequently, to expanding image quality research toward studying image viewing behavior during image evaluation tasks and task-free viewing via gaze tracking to record eye fixations^{36,37,38,39,40,41,42}. The results showed that image quality metrics can be improved by considering visual attention data³⁷. At the same time, observations highlighted the importance of higher level information about scene objects and user experience when defining ROI^{40,41,43,44}. It was found, that fixation maps did not fully coincide with the user defined ROI during image evaluation for quality or importance^{41,45}, and the highest improvement in image quality metrics can be obtained using fixations recorded not during judging image quality, but in a task-free viewing condition⁴⁶.

3. INDIVIDUAL DIFFERENCES IN IMAGE VIEWING AND EVALUATION

3.1. Individual differences in quality judgments

Individual differences in quality judgments have been the subject of research in several studies ^{11,18,47,48,49}. In particular, significant differences were observed between expert and non-expert viewers, underscoring the role of prior knowledge and experience in detecting and assessing various image artifacts.

Here we present results for image quality modeling for individual observers based on feature extraction using data obtained in a previously reported study⁴⁸. In that study subjects evaluated 126 color images of varying quality presented on a monitor screen.

Feature	SubjectR	SubjectI	SubjectL	SubjectRk	SubjectC	Avg data
maxL	-0.39	-0.64	-0.34	-0.63	-0.40	-0.47
minL	-0.64	-0.40	-0.86			
average L					0.20	
average L/ Bckgr	0.30	0.25		0.34	0.24	0.19
maxC		0.38	0.69		0.35	0.37
stdevC	0.59					
range contrast				0.35	0.39	0.45
sp.frequency ratio		0.25	0.29	0.54		0.25
edge contrast			-1.00			
max horizontal gradient	0.66	0.40	0.92		0.28	0.36
min horizontal gradient		-0.33	-0.38			
edge width				-0.51		
edge sharpness	0.36	0.51	0.63	0.89	0.26	0.53
color area contrast				0.48		
R ²	0.53	0.44	0.53	0.52	0.573	0.56

Table 1.	Image	quality	prediction	based o	n comp	outed f	eatures	with	non-zero	coefficients

Table 1 lists weighted feature combinations selected through multiple linear regressions to predict image quality ratings for five individual observers and for the ratings averaged among all observers. As evident from this table, individual predictions assessed via R^2 were similar to the averaged data, wherein the feature combinations varied in each case. Based on these data it can be suggested that different subjects are selectively tuned to specific image features and weigh them differently. A tendency to differently weigh various attributes in overall image quality rating between viewers has been shown previously⁴⁷ making the explanation plausible.

3.2. Individual differences in visual harmony

Important differences between observers were found in evaluating images along aesthetic dimensions. As an example, we are providing individual data from an experiment, where we collected scores for visual harmony for thirty four simplified images produced by pixelating high resolution images of diverse content as explained elsewhere⁵⁰. Figure 1 below plots individual ratings for two different subjects, S1 and S2, as a function of edge contrast computed from the image data. From the results, a conclusion can be made that these two subjects have probably based their judgements to a significant extent on the edge contrast with the R^2 equal or higher 0.60 for both of them. However, there is a clear difference between the subjects. While for S1 (the left-hand side of the graph) the correlation between harmony and the edge contrast is negative, with the lower perceived harmony corresponding to the higher edge contrast, S2 data (the right-hand side of the graph) show positive correlation between harmony and the edge contrast. If the data for these two subjects were averaged together, we would not be able to establish this relationship.



Figure 1.Individual harmony scores for two subjects (Y) versus edge contrast (X) based on the data obtained in⁵⁰.

3.3. Individual differences in image viewing

There is an increasing interest in understanding individual differences in image viewing behavior. Such differences were recorded in a study where observers were asked to view images selected to represent five different categories, e.g. *handshake* (two people standing near each other, shaking hands); *main object in uncluttered background* (a prominent object around the center of the image, on an uncluttered background); *crowd* (cluttered scenes with many people); *landscape* (natural landscapes, without people); and *miscellaneous* (still lives, and people)⁵¹. Dissimilar eye fixation patterns among observers were found for landscapes, crowd and miscellaneous images, while consistent fixation patterns were found for the object and handshake categories.

Aiming to explain individual variations in eye movements, a recent study⁵² discovered that individual differences in human saccadic eye movements were relatively stable across images varying in format, content and quality. These patterns according to the authors reflect systematic endogenous factors that differ across individuals but are stable within an individual from one viewing situation to another. In another publication ⁵³ the observers' gender appears to play a role in gaze behavior through modulating top-down influences on visual attention. It was found that during watching and listening video clips, men gazed more often at the mouth while women fixated the eyes of the speaker.

This discrepancy hypothetically arises from different integration strategies of visual cues in selecting the target of attention between men and women.

4. PREFERENCES, AESTHETICS AND EMOTIONS

With the ability to create high quality images, their proliferation on the Internet, and a wide range of available manipulations scientists turn to investigating why certain images are more attractive than others: is it because of their aesthetic quality, or because users are interested in the subject matter? Do generic images evoke a detectable emotional response that can be reliably predicted? Which images do people remember readily and which do they easily forget? Questions like that shift the research focus more and more onto a user and their reactions: toward the domain of psychology.

Shimojo⁵⁴ studied behavioral and neural correlates of a preference decision in free observation of different object categories (such as faces and natural scenes) depending on the level of familiarity and novelty acquired during the experiment. The results showed that the observer's gaze is biased towards the to-be-chosen stimulus (e.g. face) long before they are consciously aware of the decision ("gaze cascade effect"). Also, both novelty and familiarity causally contributed to preference, but differently across object categories. Chu et al.⁵⁵ have found that viewers rated images as having significantly higher interestingness when the faces of people on the images were morphed with their own face, or with the faces of celebrities or their colleagues. Interestingness was further increased when the scene context was less familiar. Other papers discussed preferences in the context of color selection^{27,56}.

High technical quality standards and creative applications for consumer digital photography led to the interest and focus on aesthetics, aesthetic quality and understanding aesthetics – previously the domain of art critics, visual studies and psychology of art. Papers on aesthetics were present at the HVEI for a relatively long time (see, for example⁵⁶) but the emphasis was primarily on colors⁵⁷ or paintings or special effects in photo editing. Recently, the topics of image aesthetics and emotion received a much more prominent focus from human vision, image processing and computer vision communities^{58,59,60,61,62,63,64,65,66,67} which could easily warrant a separate review.

5. THE ROLE OF CONTENT

5.1. Image appeal

Savakis et al.⁶⁸ have proposed a concept of image appeal that they found to be particularly important for automatic albuming applications. They defined image appeal by the interest that a picture generates when viewed by thirdparty observers in situations when the viewers are faced with the need to select and rank pictures within a group corresponding to a single event. They conducted an experiment asking participants to rank pictures in groups based on their relative appeal within their group and provide comments on the factors that influenced their decision. The observers were to look at a group of pictures from a single event and respond with a selection of which picture should receive the most attention in a photo album which was then assigned the maximum appeal number. Other pictures within the group were ranked in comparison to that emphasis picture. Using participants' comments, a list of both positive and negative influences was compiled and the influences were grouped into categories related to people, composition, subject, and objective metrics (colorfulness, brightness, lighting, blur, contrast, etc.). They concluded that image appeal is related to image quality only with respect to the influences in the category of objective metrics, while the majority of influences that are much more significant belong to the categories of people, composition, and subject, and therefore a new set of metrics are needed.

The significance of this study was in that it pointed out the "wrong" vector of existing image quality metrics if we were to develop applications that help people select and share images. The content should be a key factor.

5.2. Image quality and the Facebook phenomenon

In February 2011 for the first time Facebook allowed to store high resolution photos increasing the size to 2048 pixels on the largest edge. The progression from 2009 to 2011 is illustrated in Figure 2 below. Since then Facebook continues to increase picture quality and now allows full screen viewing.



Figure 2. Progressive change of stored picture size on Facebook.

However, if we look back at the 2010 data – there were 3+ billion photo uploads per month with the estimated 36 billion photo uploads per year. People were sharing and printing their images notwithstanding the resolution and quality.

This meant they were ready to trade off image quality for something more valuable.

5.3. Image Value

How to define value? According to WorldNet and The American Heritage® Dictionary of the English Language

VALUE is:

n 1: a numerical QUANTITY measured or assigned or computed; "the value assigned was 16 milliseconds"

2: the **QUALITY** (positive or negative) that renders something desirable or valuable; "the Shakespearean Shylock is of dubious value in the modern world"

3: the amount (of **MONEY** or goods or services) that is considered to be a fair equivalent for something else; "he tried to estimate the value of the produce at normal prices" [syn: economic value]

4: Worth in USEFULNESS or importance to the possessor; UTILITY or merit: the value of an education.

5: an IDEAL accepted by some individual or group; "he has old-fashioned values"

v 1: HOLD DEAR; "I prize these old photographs" [syn: prize, treasure, appreciate]

These definitions point toward several aspects of value and interestingly, image value, with the emphasis on a personal emotional connection (see v 1).

In order to understand the relationship between image value and image quality we conducted a pilot experiment asking 5 participants to evaluate image value of their own images (how valuable an image is for you?) captured in a 4 week- period. All images photographed during that period were included in the evaluation. We also pre-screened our participants to ensure they had photographed events in their lives. In addition we also collected image quality judgments from a group of 4 observers experienced in judging image quality. All evaluations were done on a 100-

point scale. Figure 3 illustrates the relationship between the rating of image value and image quality. Based on these results we can suggest that image value and image quality are different concepts. They seem to capture different "realities", and therefore, as suggested by Savakis et al.⁶⁸ we need different approaches to study them. We believe that in this line of inquiry the focus will be on the user and the full spectrum of the user imaging experience. We would like to call it the psychology of images.



Figure 3. The ratings of image value (Y) versus image quality (X).

REFERENCES

- Chandler, D.M., "Seven challenges in image quality assessment: past, present, and future research", *ISRN Signal Processing*, <u>http://dx.doi.org/10.1155/2013/905685</u> (2013).
- [2] Allnatt, J.W., "Transmitted-picture assessment", John Wiley and Sons, New York (1983).
- [3] Prosser, R.D., Allnatt, J.W. & Lewis, N.W., "Quality grading of impaired television pictures", Proc. IEE, 11, 491-502 (1964).
- [4] ITU-R Recommendation BT.500-13: *Methodology for the Subjective Assessment of the Quality of Television Pictures*. Internet address: http://www.itu.int/publ/R-REC/en (2012).
- [5] Ridder, H. de, "Subjective evaluation of scale-space image coding". In: Human Vision, Visual Processing, and Digital Display II, B.E. Rogowitz, M.H. Brill, J.P. Allebach (Eds), Proc. SPIE 1453, 31-42 (1991).
- [6] Ridder, H. de, "Minkowski-metrics as a combination rule for digital-image-coding impairments". In: Human Vision, Visual Processing, and Digital Display III, B.E. Rogowitz, J.P. Allebach, S.A. Klein (Eds), Proc. SPIE 1666, 16-26 (1992).
- [7] Watson, A.B., "Efficiency of a model human image code", JOSA A, 4, 2401-2417 (1987).
- [8] Redi, J.A. & Heynderickx, I., "Image integrity and aesthetics: towards a more encompassing definition of visual quality", In: *Human Vision and Electronic Imaging XVII*, B.E. Rogowitz, T.N. Pappas & H. de Ridder (Eds), Proc. SPIE 8291, 15-25 (2012).
- [9] Keelan, B., "Handbook of image quality: characterization and prediction", Marcel Dekker Inc., NY, USA (2002).

- [10] Rogowitz, B.E., Pappas, T.N. & Allebach, J.P. "Building bridges between human vision and electronic imaging: a ten-year retrospective", In: *Human Vision and Electronic Imaging III*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3299, 2-15 (1998).
- [11] Westerink, J.H.D.M. "Influences of subject expertise in quality assessment of digitally coded images", SID International Symposium Digest of Technical Papers, 20, 124-127 (1989).
- [12] Lloyd, C.J. & Beaton, R.J. "Design of a spatial-chromatic human vision model for evaluating full-color display systems". In: *Human Vision and Electronic Imaging: Models, Methods, and Applications*, B.E. Rogowitz, J.P. Allebach (Eds), Proc. SPIE 1249, 23-37 (1990).
- [13] Daly, S.J. "Visible differences predictor: an algorithm for the assessment of image fidelity". In: *Human Vision, Visual Processing and Digital Display III*, B.E. Rogowitz (Ed), Proc. SPIE 1666, 2 (1992).
- [14] Taylor, C.C., Pizlo, Z., Allebach, J.P. & Bouman, C.A. "Image quality assessment with a Gabor pyramid model of the human visual system". In: *Human Vision and Electronic Imaging II*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3016, 58 (1997).
- [15] Watson, A. B. "Toward a perceptual video-quality metric". In: *Human Vision and Electronic Imaging III*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3299, 139 (1998).
- [16] Carney, T., Tyler, C. W., Watson, A. B., Makous, W., Beutter, B., Chen, C. C., and Norcia, A. M. "Modelfest: first year results and plans for year two". In: *Human Vision and Electronic Imaging V*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3959, 140 (2000).
- [17] Ninassi, A., Le Meur, O., Le Callet, P., and Barba, D. "On performance of human visual system based image quality assessment metric using wavelet domain". In: *Human Vision and Electronic Imaging XIII*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 6806 (2008).
- [18] Silverstien, D.A and Farrell, J.E. "The relationship between image fidelity and image quality". *Proceedings* of the 3rd IEEE International Conference on Image Processing, 881-884 (1996).
- [19] Bartleson, C.J. "Some observations on the reproduction of flesh colors". Photographic Science and Engineering, 6, 1, 19–25 (1962).
- [20] Bartleson, C. J., & Bray, C. P. "On the preferred reproduction of flesh, blue-sky, and green-grass colors". *Photographic Science and Engineering*, 6, 19-25 (1962).
- [21] Hunt, R. W. G., "Chromatic adaptation in image reproduction," Color: Research and Application, 7, 46-49 (1982).
- [22] Hunt, R.W.G. "The Reproduction of Colour", The Wiley-IS&T Series in Imaging Science and Technology, 6th edition, 173-177 (2004).
- [23] Siple, P. & Springer, R.M. "Memory and preference for colors of objects". *Perception & Psychophysics*, 34 (4), 363-370 (1983).
- [24] De Ridder, H., Blommaert, F.J.J., and Fedorovskaya, E.A. "Naturalness and image quality: chroma and hue variation in color images of natural scenes". In: *Human Vision, Visual Processing, and Digital Display VI*, B.E. Rogowitz & J.P. Allebach (Eds), Proc. SPIE 2411, 51 (1995).
- [25] Fedorovskaya, E. A., De Ridder, H., Blommaert, F. "Chroma variations and perceived quality of color images of natural scenes". *Color Research and Application*, 22, 96-110 (1997).
- [26] Yendrikhovski, S.N., Blommaert, F.J.J. and De Ridder, H. "Perceptually optimal color reproduction". In: *Human Vision and Electronic Imaging III*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3299, 274 (1998).
- [27] Koh, C. C., Foley, J.M., and Mitra, S. K. "Color preference and perceived color naturalness of digital videos". In: *Human Vision and Electronic Imaging III*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 6057, (2006).

- [28] Kuijsters, A., Lambooij, M., Ijsselsteijn, W. A., and Heynderickx, I. E. J. Influence of chroma variations on naturalness and image quality in stereoscopic images, In: Human Vision and Electronic Imaging XIV, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 7240, (2009).
- [29] Janssen, T. J. W. M. & Blommaert, F. J. J. "Information-processing approach to image quality". In: *Human Vision and Electronic Imaging V*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3959, (2000).
- [30] Bradley, A. P. "Can region of interest coding improve overall perceived image quality?" In: APRS Workshop on Digital Image Computing (WDIC'03), B. Lovell, & A. Maeder (Eds.), The University of Queensland, 1, 41 (2003).
- [31] Vu, C., Larson, E. and Chandler, D. M. "Visual Fixation Patterns when Judging Image Quality: Effects of Distortion Type, Amount, and Subject Experience," In: 2008 Southwest Symposium on Image Analysis and Interpretation (2008).
- [32] Sadaka, N.G., Karam, L.J., Ferzli, R., & Abousleman, G.P. "A no-reference perceptual image sharpness metric based on saliency-weighted foveal pooling," In: *ICIP 2008, 15th IEEE International Conference on Image Processing*, 369-372 (2008).
- [33] Tong, Y., Konik, H., Cheikh, F.A., & Tremeau, A. "Full reference image quality assessment based on saliency map analysis", *Journal of Imaging Science and Technology*, 54, 3, 1-14 (2010).
- [34] Itti, L., Koch, C., & Niebur, E. "A Model of Saliency-Based Visual Attention for Rapid Scene Analysis". In: *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20, 11, 1254-1259 (1998).
- [35] Itti, L., Koch, C. "Comparison of feature combination strategies for saliency-based visual attention systems". In: *Human Vision and Electronic Imaging IV*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3644, 473 (1999).
- [36] Redi, J., Liu, H., Gastaldo, P., Zunino, R., & Heynderickx, I. "How to apply spatial saliency into objective metrics for JPEG compressed images?" In: *Proceedings of the 16th IEEE international conference on Image processing (ICIP'09)*, Magdy Bayoumi (Ed.), IEEE Press, Piscataway, NJ, USA, 957-960 (2009).
- [37] Liu, H. & Heynderickx, I. "Studying the added value of visual attention in objective image quality metrics based on eye movement data". In: *Proceedings of the 16th IEEE international conference on Image* processing (ICIP'09), Magdy Bayoumi (Ed.), IEEE Press, Piscataway, NJ, USA, 3061-3064 (2009).
- [38] Larson, E. C. & Chandler, D. M., "Unveiling Relationships Between Regions of Interest and Image Fidelity Metrics," Proc. SPIE Visual Communications and Image Processing 2008, San Jose, CA (2008).
- [39] Kadiyala, V., Pinneli, S., Larson, E. C. & Chandler, D. M. "Quantifying the Perceived Interest of Objects in Images: Effects of Size, Location, Blur, and Contrast." In: *Human Vision and Electronic Imaging XIII*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 6806 (2008).
- [40] Moorthy, A. K. & Bovik, A. C. "Perceptually significant spatial pooling strategies for image quality assessment". In: *Human Vision and Electronic Imaging XIV*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7240 (2009).
- [41] Wang, J., Chandler, D.M, & Le Callet, P. "Quantifying the relationship between visual salience and visual importance". In: *Human Vision and Electronic Imaging XV*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7527 (2010).
- [42] Judith, J., Liu, H., Rodolfo Zunino, R., & Heynderickx, I. "Interactions of visual attention and quality perception". In: *Human Vision and Electronic Imaging XVI*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7865 (2011).
- [43] Navalpakkam, V. & Itti, L. "Combining bottom-up and top-down attentional influences". In: Human Vision and Electronic Imaging XI, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 6057 (2006).
- [44] Itti, L. & Baldi, P. F. "Bayesian Surprise Attracts Human Attention", Vision Research, 49, 10, 1295-1306 (2009).

- [45] Babcock, J. S., Pelz, J. B. & Fairchild, M. D. "Eye tracking observers during color image evaluation tasks". In:, *Human Vision and Electronic Imaging VIII*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 5007 (2003).
- [46] Larson, E. C., Vu, C. T. & Chandler, D. M. "Can visual fixation patterns improve image fidelity assessment?" In: *Proceedings of the 15th IEEE international conference on Image processing* (2008).
- [47] Heynderickx, I.E. & Bech, S. "Image quality assessment by expert and non-expert viewers". In: Human Vision and Electronic Imaging VII, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 4662 (2002).
- [48] Fedorovskaya, E. A. "Image Quality as a Problem of Computational Vision". In: Proceedings of IS&T's PICS Conference, 22-28 (2003).
- [49] Speranza, F., Poulin, F., Renaud, R., Caron, M., & Dupras, J. "Objective and subjective quality assessment with expert and non-expert viewers," In: *Quality of Multimedia Experience (QoMEX)*, 2010 Second International Workshop, 46-51 (2010).
- [50] Fedorovskaya, E.A., Neustaedter, C., & Hao, W. "Image harmony for consumer images". In: Proceedings of the IEEE International Conference on Image Processing (ICIP 2008), IEEE Press, 121-124 (2008).
- [51] Jaimes, A., Pelz, J.B., Grabowski, T., Babcock, J.S., & Chang, S.F. "Using human observer eye movements in automatic image classifiers". In: *Human Vision and Electronic Imaging VI*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 4299, 373 (2001).
- [52] Castelhano, M. S. & Henderson, J.M. "Stable individual differences across images in human saccadic eye movements". Canadian Journal of Experimental Psychology, 62(1), 1-14 (2008).
- [53] Shen, J. & Itti, L. "Top-down influences on visual attention during listening are modulated by observer sex", Vision Research, 65, 62-76 (2012).
- [54] Shimojo, S. "Behavioral and neural correlates of visual preference decision". In: Human Vision and Electronic Imaging XIV, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7240 (2009).
- [55] Chu, S. L., Fedorovskaya, E., Quek, F. & Snyder, J. "The effect of familiarity on perceived interestingness of images". In: *Human Vision and Electronic Imaging XVIII*, B.E. Rogowitz, T.N. Pappas & H. De Ridder (Eds), Proc. SPIE 8651 (2013).
- [56] Stephen E. Palmer, Karen B. Schloss, Human preference for individual colors, Proc. SPIE 7527, Human Vision and Electronic Imaging XV, (2010)
- [57] Vasile, A. & Bender, W. R. "Image query based on color harmony". In: Human Vision and Electronic Imaging VI, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 4299 (2001).
- [58] Fedorovskaya, E. A., Prabhu, G., Horwitz, C., Matraszek, T., Parks, P. & Endrikhovski, S. "Affective imaging for future generation interactive imaging systems". In: *Human Vision and Electronic ImagingVI*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 4299 (2001).
- [59] Black, J. A. Jr., Kahol, K., Tripathi, P., Panchanathan, S., & Kuchi, P. "Indexing natural images for retrieval based on Kansei factors". In: *Human Vision and Electronic Imaging IX*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 5292 (2004).
- [60] Daly, S.J. "On the role of artistic intent of image quality". In: Human Vision and Electronic Imaging XIII, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 6806 (2008).
- [61] Palmer, S. "Aesthetic science: understanding human preferences for spatial composition". In: *Human Vision and Electronic Imaging XIV*, Proc. SPIE 7240 (2009).
- [62] Graham, D.J., Friedenberg, J., Rockmore, D.N., & Field, D. "Intensity statistics of artwork: connections to human visual perception". In: *Human Vision and Electronic Imaging XV*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7527 (2010).

- [63] Cerosaletti, C. D., Hao, W., Gallagher, A. & Loui, A. "Investigating Two Features of Aesthetic Perception in Consumer Photographic Images: Clutter and Center". In: *Human Vision and Electronic Imaging XVI*, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 7865 (2011).
- [64] Floris L. van Nes. "Aesthetics versus utility in electronic imaging". In: Human Vision and Electronic Imaging XIII, B.E. Rogowitz & T.N. Pappas (Eds), Proc. SPIE 6806 (2008).
- [65] Daniel J. Graham, Jay D. Friedenberg, Cyrus H. McCandless, Daniel N. Rockmore, Preference for art: similarity, statistics, and selling price, Proc. SPIE 7527, Human Vision and Electronic Imaging XV, (2010).
- [66] Redi, J.A. & Heynderickx, I. "Image integrity and aesthetics: towards a more encompassing definition of visual quality". In: *Human Vision and Electronic Imaging XVII*, B.E. Rogowitz, T.N. Pappas & H. de Ridder (Eds), Proc. SPIE 8291 (2012).
- [67] Joshi, D., Datta, R., Fedorovskaya, E., Luong, Q.-T., James Z. Wang, J. Z., Li, J., & Luo, J. "Aesthetics and Emotions in Images", *IEEE Signal Processing*, 28, 5, 94-115 (2011).
- [68] Savakis, A. E., S. Etz, S., and Loui, A. "Evaluation of image appeal in consumer photography". In: *Human Vision and Electronic Imaging V*, B.E. Rogowitz, T.N. Pappas (Eds), Proc. SPIE 3959 (2000).