Saliency Models as Gamut-Mapping Artifact Detectors

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Abstract

When an image is reproduced with a device different artifacts can occur. These artifacts, if detectable by observers, will reduce the quality of the image. If these artifacts occur in salient regions (regions of interest) or if the artifacts introduce salient regions they contribute to reduce the quality of the reproduction. In this paper we propose a novel method for the detection of artifacts based on saliency models. The method is evaluated against a set of gamut mapped images containing the most common artifacts, which have been marked by a group of color experts. The results have shown that the proposed metrics are promising to detect the artifacts through the reproduction.

Introduction

For centuries researchers have been trying to achieve accurate reproductions of images. Technological advancements have taken us closer and closer to this goal, but still it has not been reached. When we reproduce an image several issues, such as the limited number of colors a system can reproduce, contribute to the quality of the reproduction. One of the attributes which influences image quality greatly is artifacts. We will focus on the reproduction of images in a print work flow, more specifically the gamut mapping process. When we gamut map an image several artifacts may occur, such as contouring, loss of details, and halos. These artifacts contribute to reducing the quality of an image if detectable [1–3]. One way of detecting them is a visual inspection of the image. However, this might be time consuming and resource demanding. Because of this objective evaluation methods have been proposed. There have been proposed several objective methods, commonly referred to as image quality metrics [4]. These traditional metrics such as MSE and PSNR, are not credible for evaluating the image quality when the artifacts are introduced. This is due to the fact that the metrics do not take the characteristics of the Human Visual System (HVS) into account. The goal of this paper is to detect gamut mapping artifacts. In order to achieve this goal we propose a novel method based on saliency. We limit in this paper our method to detection of loss of details and contouring in shadow regions, where the artifacts are usually most perceivable and detectable.

This paper is organized as follows: first we present state of the art, then a section on the applicability of saliency maps to gamut mapping artifacts, before we introduce a new method for using saliency models to detect gamut mapping artifacts. Experimental results are shown before we conclude.

State of the art

Artifacts

The artifacts found in an image from a reproduction system can severely degrade the quality of an image, and is considered as one of the major attributes contributing to influencing image quality [4, 5]. Several researchers have stated the importance of artifacts for color printing; Bonnier et al. [6] found that artifacts strongly influence the quality of gamut mapped images. In an experiment by Hardeberg et al. [7] observers stated loss of shadow details as the most important criteria for the evaluation of gamut mapped images. Pedersen and Hardeberg [4] evaluated a color work flow, and found that observers looked for artifacts in almost 40 percent of the images they evaluated. Evaluating images in a psychovisual test is time consuming and requires a lot of observers. Hence researchers aim at automated evaluation with image quality measures. As states [1], metrics of image quality based on detecting artifacts are much more complex than those based on image fidelity. But artifacts strongly affect observers' preferences. If they occur in the image, measures based on fidelity are usually too weak to model quality of considered images.

There has been little recent research on detecting artifacts caused by gamut mapping. Contouring artifacts can be partially identified using methods for finding blocking artifacts in JPEG-compressed images, e.g. [8] Another typical artifact caused by gamut mapping, loss of details, can be probably better handled by structural image quality measures. A recent paper by Zolliker and Simon [9] also discussed removing loss of details artifacts by applying unsharp masking. However this technique cannot be directly used to detect those artifacts. We extend the previous work by integrating the saliency maps with an emphasis in artifact detection.

Saliency map

Visual Saliency is the perceptual quality that makes an object, person, or pixel region stand out relative to its neighbors and thus capture our attention. Visual attention results both from fast, pre-attentive, bottom-up visual saliency of the retinal input, as well as from slower, top-down memory and volition based processing that is task-dependent [10].

Saliency estimation methods can broadly be classified as biologically based, purely computational, or a combination of both. In general, all methods employ a low-level approach by determining contrast of image regions relative to their surroundings, using one or more features of intensity, color, and orientation. [11] Many models have been proposed based on these low-level features and almost all have a low resolution and ill-defined object boundary [12–14]. A recent model [11] outperforms the rest in that it is able to efficiently output full resolution saliency maps, establish well-defined boundaries of salient objects and disregard high frequencies arising from texture, noise and blocking artifacts.

In brief, this saliency detection algorithm applies the Difference-of-Gaussian (DoG) filter for band pass filtering. The DoG filter is widely used in edge detection and is suitable for detecting the artifacts due to the contouring effect in our context.

The DoG filter is given by:

$$DoG(x,y) = \frac{1}{2\pi}[\frac{1}{\sigma_1^2}e^{-\frac{x^2+y^2}{2\sigma_1^2}} - \frac{1}{\sigma_2^2}e^{-\frac{x^2+y^2}{2\sigma_2^2}}] = G_1(x,y,\sigma_1) - G_2(x,y,\sigma_2),$$

where σ_1 and σ_2 are the standard deviation of the gaussian distribution. In order to ensure the salient regions will be fully covered and not just highlighted on edges or in the center of the regions, we drive σ_1 to infinity. This results in a notch in frequency at DC component while retaining all other frequencies. To remove high frequency noise and textures, we use a small Gaussian kernel keeping in mind the need for computational simplicity. For small kernels, the binomial filter approximates the Gaussian very well in the discrete case. We use 1/16[1, 4, 6, 4, 1] giving $\omega_{hc} = \pi/2.75$.

The method of finding the saliency map S for an image I of width W and height H pixels can thus be formulated as:

$$S(x,y) = \|I_\mu - I_{\omega_{hc}}(x,y)\|, \quad (1)$$

where I_μ is the mean image feature vector, $I_{\omega_{hc}}(x,y)$ is the corresponding image pixel vector value in the Gaussian blurred version (using a 5 x 5 separable binomial kernel) of the original image, and $\|\|$ is the L_2 norm. Using the Lab color space, each pixel location is an $[L,a,b]^T$ vector, and the L_2 norm is the Euclidean distance. We have the images transformed into CIELAB space to take the effect of lightness on saliency into account. An illustration of saliency detection over the original can be found in Figure 1

Figure 1: The original image and its corresponding saliency map.

Applicability of Saliency Maps to Gamut Mapping Artifacts

If an artifact is detectable in the image, it should be salient, and therefore saliency models should be applicable for detecting artifacts. If salient regions are lost, such as important details in the images, there will be a difference in saliency between the original and reproduction. Also in this case saliency models should be able to detect artifacts.

The first step to ensure that saliency maps are applicable to detect artifacts is to investigate the saliency maps from gamut mapped images. We have computed the saliency map for an original image and a gamut mapped image (Figure 2). In the gamut mapped image significant loss of details occur, being one of the artifacts we focus on. Investigation of the saliency maps show that they are not similar, and that the saliency changes even though the image is the same. In this case the saliency maps have been computed over the entire image. The results indicate that a difference of saliency can be suitable for detecting artifacts.

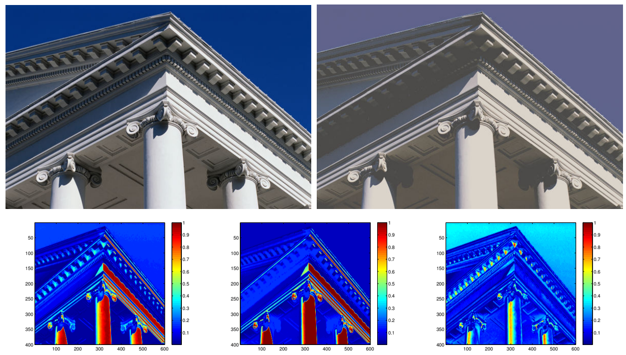


Figure 2: The illustration of different gamut-mapped images and their corresponding saliency maps. The first row shows the original image and the gamut mapped version with loss of details. In the next row the saliency map of the original is on the left, in the middle the saliency map of the gamut mapped version of the original. The right image shows the normalized absolute difference in saliency between the two normalized saliency maps. As we can see the original and the gamut mapped version have difference salient regions, indicating that a change of saliency can be used to detect artifacts.

Experimental Framework: Saliency models as artifact detectors

We propose a framework for using saliency models for the detection of gamut mapping artifacts. Two different approaches, one global and one local, are explained in details below.

Global strategy

The global approach is very straightforward as explained above. We detect saliency for the original and gamut mapped image directly and then derive the difference between the two saliency maps. An adaptive thresholding with the Otsu's method, which chooses the threshold to minimize the intraclass variance of the black and white pixels, is used to locate the regions where the artifacts lie in the difference image [15]. Figure 3 show the steps of the global approach. The method can also be illustrated by the following formula,

$$D(x,y) = S(x,y) - S(x_g,y_g), \quad (2)$$

where $S(x,y)$ is the saliency map derived from Equation 1 and $S(x_g,y_g)$ is the saliency map upon the gamut-mapped image. $D(x,y)$ is the difference image which shows the artifacts by the global strategy.

We illustrate the global method in Figure 4. For the images in the first row, the biggest difference of the gamut mapped image from the original is the loss of details in the eagle's body. The saliency model is able to detect the attention shift due to the reproduction and give us the right result.

The contouring dominates the artifacts in the second row of images. However, since the heart of flower has a big color contrast from the background and attracts much of the attention, the saliency model will tell the difference in this region. It shows the inadequacy of the artifact detection using global approach and leads us to further investigate the image in specific regions. We build on the global strategy by using the saliency maps in local regions.

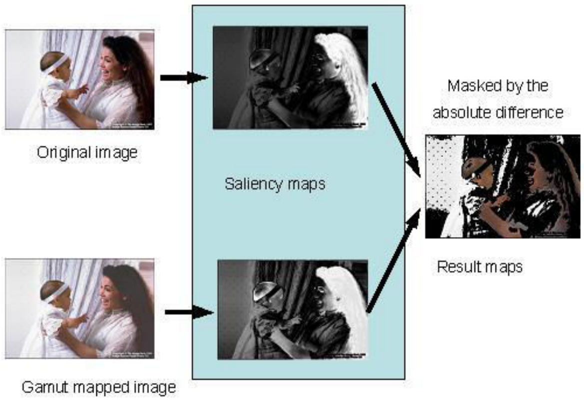


Figure 3: The experimental framework using the global method. Saliency maps are created of both the original and reproduction, and the absolute different between these two maps are taken to get an indication of where artifacts occur.

The artifact detection based on the global saliency gives a rough illustration of where they are, but it can be misleading since it is always difficult to set the threshold to extract the artifact regions from the background. Some regions equally attract much attention from the original to the reproduction and we cannot obtain the salient shift. Therefore we are required to pick out the errors from the specific regions.

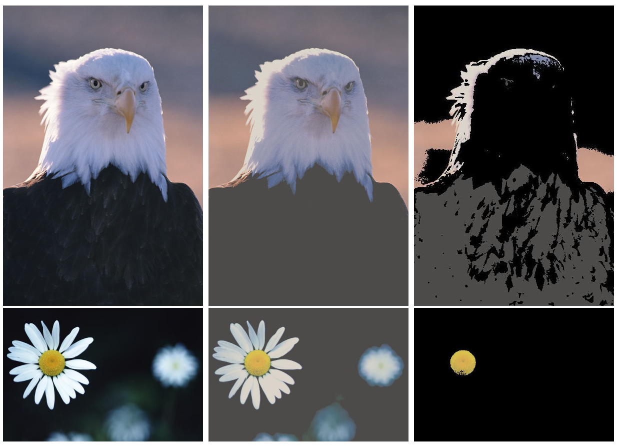


Figure 4: The original images are listed in the left column, the gamut mapped ones are in the middle and the results from the global method are shown on the right. For the first row, the global saliency detection generally tells where the artifacts lie. However, in the next row, the heart of flower stands out of both original and reproduced image. The global thresholding is no longer sufficient to detect the artifacts.

Local strategy

The local strategy is shown in Figure 5, and is as follows: The original image is firstly transformed into the CIELAB color space considering about its lightness, and then the mean-shift clustering [16] is applied on the images. Using the CIELAB color space, each pixel is represented in [L* a* b*] vectors, which means the lightness and chromatic values are separated. In this way, we are able to investigate the influence of color in different lightness levels. The mean-shift algorithm is a nonparametric clustering technique which is commonly used for edge preserving and image segmentation. It does not require prior knowledge of the number of clusters, the constrain of the shape of the clusters and it provides better boundary. The spatial band width is set as 3 and the range band width is 1.

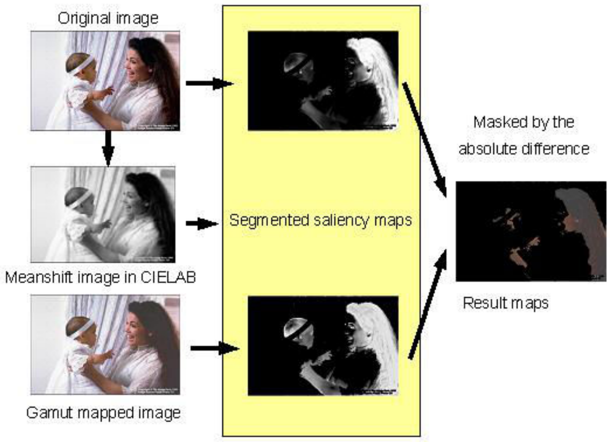


Figure 5: The experimental framework using the local method. By using the original image a mask is created with the meanshift algorithm in the CIELAB colorspace. This mask is used together with the saliency models to create segmented saliency maps of both the original and reproduction. Then the absolute difference of these two maps are taken to find artifacts.

With an adaptive threshold, the image could be separated into several parts allowing for the analysis of specific artifacts in different lightness level. In the case of detail loss, which is a problem in shadow and highlight areas, especially in gamut mapping, the image can be divided into two parts. One part generally contains the high lightness while the other is low lightness. Due to the shadow effect, we tend to have more focus on the regions in low lightness distribution. The adaptive thresholding is applied onto the mean-shift transformed image of the original. The same mask partitioning the original image will also be used to filter the reproduction, ensuring a correct comparison of regions. Then, the saliency detection is applied and the difference is extracted upon the segmented regions to show the artifact regions.
Compared with Equation 2, the artifact detection based on local strategy is shown as,

$$M = Seg(I_{lab}(x,y)), \tag{3}$$

and

$$D(x,y) = S(M(x,y)) - S(M(x_g,y_g)), \tag{4}$$

where $I_{lab}(x,y)$ is the original image transformed into CIELAB color space. *Seg* is the mean-shift filtering taking the low lightness into account, and thereby M is the mask from the original image. Equation 4 is similar to Equation 2, except we apply the same mask on both original and gamut-mapped images.

Since the global model gives too high weight on the areas that capture the attention, local regions are now taking into account in depth. We can see that, the occurrence of artifacts is much higher in the regions with low lightness than the high lightness. Therefore, we focus on detecting the artifacts in the regions with low-lightness distribution. Figure 6 show that we are able to obtain the regions where the artifacts occur from the model when compared against the areas agreed upon by the authors to contain artifacts.

With the local method, we are able to obtain all the artifacts in the eagle's body and its eyes for the first set. In the second set of images, the edges of the white blobs are detected by our method.

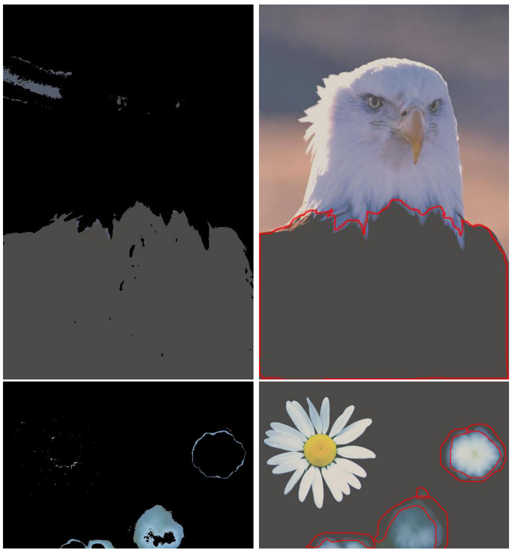


Figure 6: The images in the left column illustrate the artifacts by our local saliency detection model, and the columns are the artifacts agreed upon by the authors to contain artifacts.

Experiment Setup

In order to investigate the performance of the proposed metrics in specific, we designed a psychophysical experiment by inviting 12 expert observers to mark the exact regions where they consider the artifacts occur. The original image and the gamut-mapped were displayed side by side, which also allows the observer to zoom in and zoom out both images simultaneously. All the observers are color experts, i.e. are very familiar with the effect of gamut-mapping on color images. The experiment is performed on the monitor calibrated to its target setting, i.e. D50, Gamma 2.2, 120cd/m2, and the room light is maintained as D50 while the ambient light is measured as 5300K, the illuminance 56 lux. The test images are listed in Figure 7. Mapping of these images were mostly obtained using different clipping algorithms: clipping in the direction of focal point or the hue preserving minimum ΔE^*_{ab}. Some artifacts in the mapped images were also caused by adding or enhancing details in the process of gamut mapping.

(a) 1 (b) 2 (c) 3 (d) 4 (e) 5

(f) 6 (g) 7 (h) 8 (i) 9 (j) 10

(k) 11 (l) 12 (m) 13 (n) 14 (o) 15 (p) 16

(q) 17 (r) 18 (s) 19

Figure 7: The test images.

Evaluation

After obtaining the data in the experiment, we computed the mean artifact mask for each image, i.e.

$$\text{Mask}_{mean} = \frac{\sum_{observers} \text{Mask}_{observer}}{\text{number of observers}}. \tag{5}$$

The mean mask represents the regions in the images which were considered as the artifacts by observers. The comparison of mean masks and masks computed using saliency map is presented in the images in Table 1. White regions in the mask mean indicates that most of the observers considered these regions as artifacts, while black regions are where no artifacts occur.

As a measure of the performance for our proposed method we have used correlation. The 2-dimensional correlation between the mean masks and the result from our proposed method is computed for each image in the experiment. Let us notice, that we cannot expect very high correlations in images, where observers do not indicate similar images between each other. Hence we computed the correlation between each observer and the mean mask of other observers. The mean of these values is the measure of correlation between observers. We compare this value and the correlation between saliency map mask and the mean mask in the Table 8.

From Table 1, we can notice that in images 1, 5, 13, 14, 15, 18, and 19, the proposed metrics predict very well the location of contouring or loss of details due to gamut mapping. Also, there is a high correlation with the mean masks from the expert observers (Figure 8). We should also find that, in images 2, 4, and 17, people tend to find the artifact regions in the high lightness; therefore, and for these images we computed the saliency maps for the high lightness segments.

Figure 8 shows the correlation for the proposed method, the mean observers, and the Structural SIMilarity (SSIM) measure [17]. The proposed method has a correlation higher than 0.5 in five of the 19 images, also having a correlation higher than the mean observers. In most images the proposed method has a higher

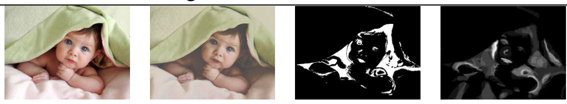
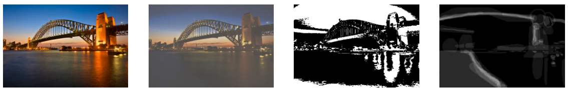
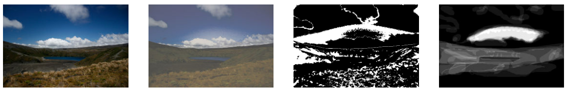
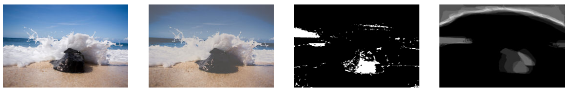
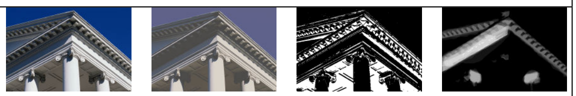
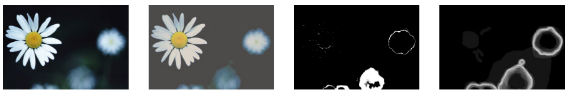
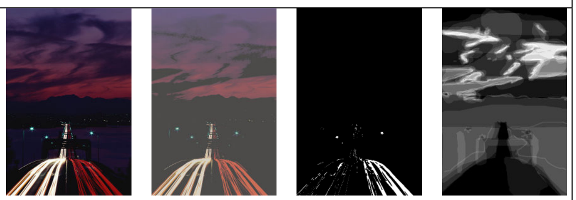
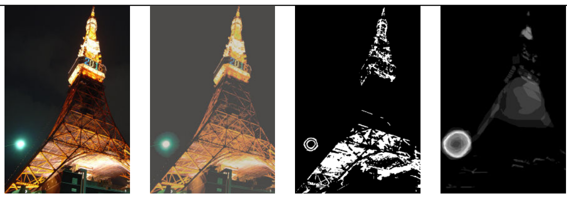
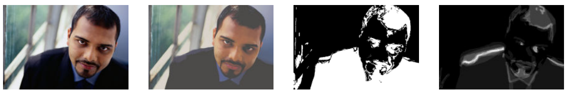
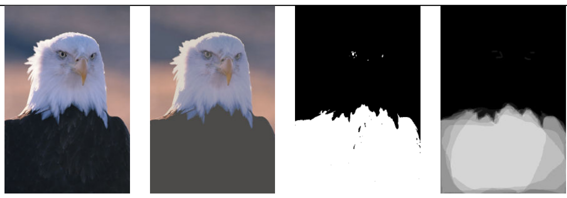
Image	Original image	Gamut-mapped image	Proposed method	Observers	Image	Original image	Gamut-mapped image	Proposed method	Observers
1					2				
3					4				
5					6				
7					8				
9					10				
11					12				
13					14				
15					16				
17					18				
19									

Table 1: Artifacts regions according to the proposed method and the mean observers' masks obtained in the experiment.

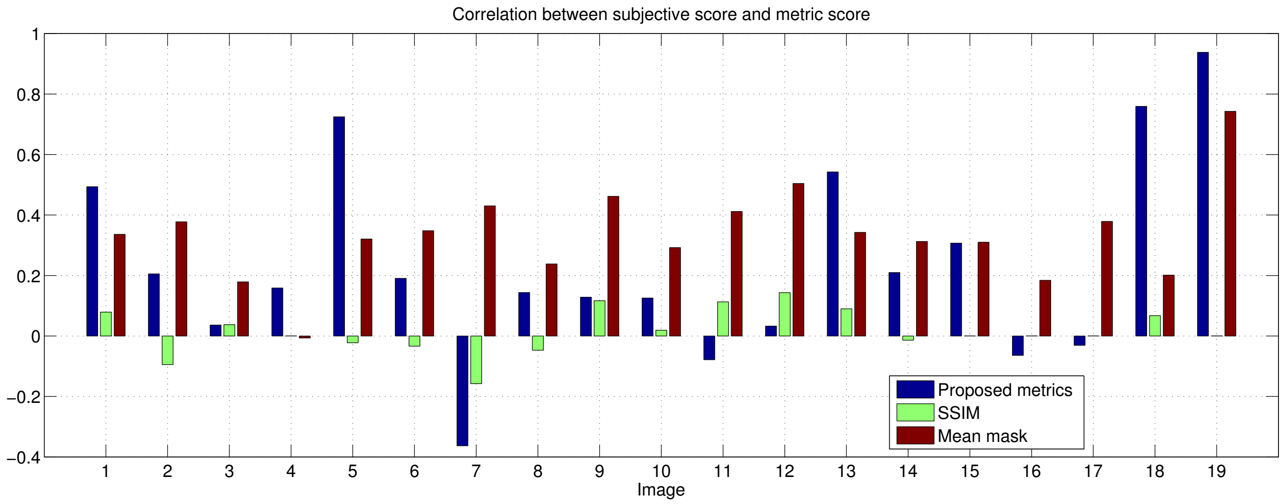


Figure 8: Correlation between the artifacts regions obtained by using the saliency map algorithm and mean observers mask, SSIM metrics [17], and the mean observers mask and the mean correlation between observers and the mean mask of other observers.

correlation than SSIM. For SSIM the results below the 0.4 quantile for a given image were considered as containing artifacts.

There are also images where the proposed method does not predict artifacts well, such as in images 7 and 16, where the wrong area is detected. In image 10 the proposed method finds larger areas with artifacts, even though the observers have marked smaller regions. Investigation of the number of pixels detected as artifacts from the proposed method and the number of pixels marked by more than 50% observers as artifacts show that our method overestimate the area with artifacts in 15 of the 19 images. This could probably be improved by finding better parameters for our algorithm.

Conclusion and future work

We have proposed a novel method based on saliency for the detection of gamut mapping artifacts. We have shown how saliency can be used to detect artifacts, where either salient regions are lost or salient regions are introduced to the image. An experiment with 12 expert observers were carried out, and the regions marked by the observers were compared against the proposed method. The results are promising, and show that our saliency algorithm can be used to detect gamut mapping artifacts.

Future work includes investigation of the parameters in order to detect artifacts more precisely.

References

[1] N. Burningham, Z. Pizlo, and J.P. Allebach. *Encyclopedia of Imaging Science and Technology*, chapter Image Quality Metrics, pages 598–616. Wiley, New York, 2002.

[2] K. Topfer, B. Keelan, S. O'Dell, and R. Cookingham. Preference in image quality modelling. In *Image Processing, Image Quality, Image Capture, Systems Conference*, pages 60–64, Apr, Portland, OR 2002. IS&T.

[3] M. Pedersen, N. Bonnier, J. Y. Hardeberg, and F. Albregtsen. Attributes of image quality for color prints. *Journal of Electronic Imaging*, 19(1):011016–1 – 011016–13, Jan 2010.

[4] M. Pedersen and J. Y. Hardeberg. Survey of full-reference image quality metrics. Technical Report 5, Gjøvik, Norway, June 2009. ISSN: 1890-520X.

[5] M. Pedersen, N. Bonnier, J. Y. Hardeberg, and F. Albregtsen. Attributes of a new image quality model for color prints. In *Color Imaging Conference*, pages 204–209, Albuquerque, New Mexico, USA, Nov 2009.

[6] N. Bonnier, F. Schmitt, H. Brettel, and S. Berche. Evaluation of spatial gamut mapping algorithms. In *14th Color Imaging Conference*, volume 14, pages 56–61. IS&T/SID, Nov 2006.

[7] J. Y. Hardeberg, E. Bando, and M. Pedersen. Evaluating colour image difference metrics for gamut-mapped images. *Coloration Technology*, 124(4):243–253, Aug 2008.

[8] G.A. Triantafyllidis, D. Tzovaras, and M.G. Strintzis. Detection of blocking artifacts of compressed still images. volume 0, page 0607, Los Alamitos, CA, USA, 2001. IEEE Computer Society. ISBN 0-7695-1183-X. doi: http://doi.ieeecomputersociety.org/10.1109/ICIAP.2001.957077.

[9] P. Zolliker and K. Simon. Retaining local image information in gamut mapping algorithms. *IEEE Transactions on Image processing*, 16, 2007.

[10] E. Niebur and C. Koch. *The Attentive Brain*. MIT Press, Cambridge MA, Octorber 1995.

[11] R. Achanta, S. Hemami, F. Estrada, and S. Süsstrunk. Frequency-tuned Salient Region Detection. In *IEEE International Conference on Computer Vision and Pattern Recognition (CVPR)*, Miami Beach, Florida, June 2009. URL `http://www.cvpr2009.org/`.

[12] Y-F. Ma and H-J. Zhang. Contrast-based image attention analysis by using fuzzy growing. In *MULTIMEDIA '03: Proceedings of the eleventh ACM international conference on Multimedia*, pages 374–381, New York, NY, USA, 2003. ACM. ISBN 1-58113-722-2. doi: http://doi.acm.org/10.1145/957013.957094.

[13] X. Hou and L. Zhang. Saliency detection: A spectral residual approach. pages 1 –8, june 2007. doi: 10.1109/CVPR.2007.383267.

[14] L. Itti, C. Koch, and E. Niebur. A model of saliency-based visual attention for rapid scene analysis. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 20(11):1254–1259, 1998. URL `citeseer.ist.psu.edu/itti98model.html`.

[15] N. Otsu. A Threshold Selection Method from Gray-level Histograms. *IEEE Transactions on Systems, Man and Cybernetics*, 9(1):62–66, 1979. doi: 10.1109/TSMC.1979.4310076. URL `http://dx.doi.org/10.1109/TSMC.1979.4310076`.

[16] D. Comaniciu and P. Meer. Mean shift: a robust approach toward feature space analysis. *Pattern Analysis and Machine Intelligence, IEEE Transactions on*, 24 (5):603–619, 2002. doi: 10.1109/34.1000236. URL `http://dx.doi.org/10.1109/34.1000236`.

[17] Z. Wang, A.C. Bovik, H.R. Sheikh, and E.P. Simoncelli. Image quality assessment: from error visibility to structural similarity. *Image Processing, IEEE Transactions on*, 13(4): 600 –612, april 2004. ISSN 1057-7149. doi: 10.1109/TIP.2003.819861.

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