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Global Contrast Factor - a New Approach to Image Contrast

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Abstract

Contrast in image processing is usually defined as a ratio between the darkest and the brightest spots of an image. In this paper we introduce a different contrast definition. The newly introduced Global Contrast Factor (GCF) corresponds closer to the human perception of contrast. GCF uses contrasts at various resolution levels in order to compute overall contrast. Experiments were conducted in order to find weight factors needed to calculate GCF. GCF measures richness of detail as perceived by a human observer, and as such can be used in various application areas like rendering, tone mapping, volume visualization, and lighting design.

1. Introduction

When processing images users often manipulate contrast, brightness, and histogram in order to improve image quality. Contrast as an image property is usually defined as ratio between the brightest and the darkest spot in the image. The human perception of the image contrast does not completely correspond to this definition. In this paper we introduce an improved contrast factor. Instead of focusing only on the ratio of the darkest and the lightest spot, we take into account local contrasts at various resolution levels. We call this new image property Global Contrast Factor (GCF). The basic concept of GCF has been introduced in [NMP02, NMP98]. In this paper we extend the initial concept towards a more complete solution based on conducted user experiments.

We call the contrast of any (small) part of an image the local contrast. The global contrast is defined as the average local contrast of smaller image fractions. An image with a high global contrast causes a global feeling of a detailed and variation-rich image. As opposed to it, an image with a lower global contrast contains less information, less details, and appears more uniform.

Figures 1 and 2 illustrate two images with significantly different global contrast factor. The waterfall image is considered to have a higher contrast than the moonlight image for most of the users.

Note that the contrast factor (as proposed) does not depend on the content of the image. It is possible to have a low-dynamics image of a high-dynamics subject. E.g. an image of a racing car might have a lower contrast, then an image of a static building.

The main idea of the paper is to compute local contrasts at various spatial frequencies, and to use these local contrasts for computation of the global contrast factor. Since our visual system is not equally sensitive to changes at various frequencies [MS74] we cannot simply compute the global contrast as the average of local contrasts. The proposed solution is to build a weighted average of local contrasts. The results of user experiments are used for the computation of the weighting function.

The remainder of the paper is organized as follows. Section 2 discusses related work, Section 3 describes how local contrasts are computed, Section 4 describes experiment setup which helped us in finding weighting factors, Section 5 describes the weighting factors and proposed solution, and Section 6 describes results.

2. Related Work

Rushmeier at al. [RWP*95] studied the difference of two grayscale images in order to evaluate the quality of rendering. The method operates in Fourier space and uses a contrast sensitivity function [MS74] to weight coefficients at various frequencies. The image difference formula uses the L_2 distance of filtered Fourier coefficients.

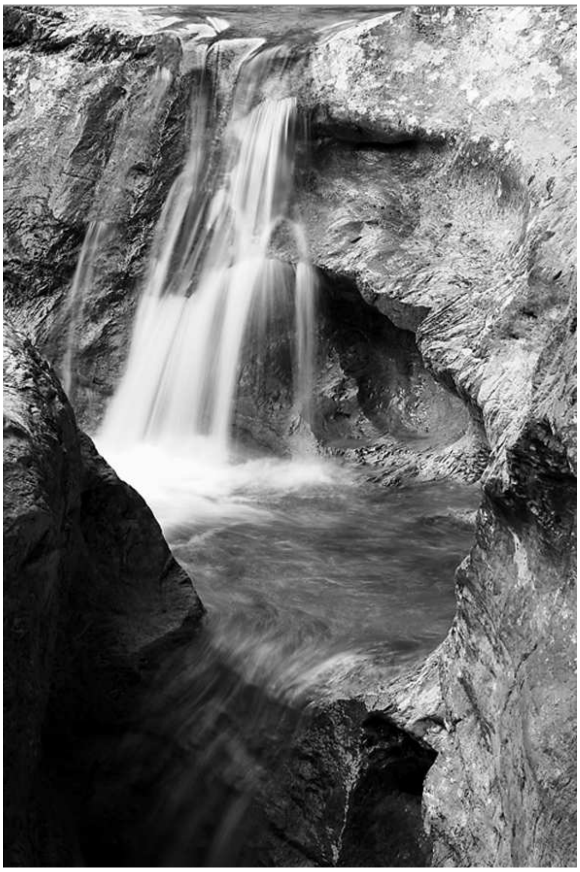

Figure 1: *An image with high GCF, rich in details*

Figure 2: *An image with lower GCF, poor at high frequency components*

Similar metrics are intended to be used with color images like Kolpatzik and Bouman [KB95] and Zhang and Wandel [ZW96], which use opponent color channels. Just like the first method these take the spatial distribution into account. Taking the color information into account results in a more complicated algorithm. It is not possible to simply scale a grayscale solution. The 3 channels have different filter profiles as the luminance filter is sharpest while the yellow-blue channel is the most blurred due to the retina structure.

Theoretical approaches should be based on information theory, which depend only on luminance histograms and do not take spatial coherence at different frequencies into account. Based on information theory the work of [FAS99, VFSH03,PSF05] defines a single scalar entropy value. It can be applied to select the best view point for a given set or to determine a pleasant lighting. Information theory can also be used to compute overall image complexity as described in [RFS05].

Gooch at al. [GRMS01] describe a quite different method for selection of the view point, ensuring an aesthetical balance of the image. The contour or silhouette lines of the objects are computed and their spatial position in a regular grid of 2 by 3 or 3 by 5 are analyzed. The latter is also applied in classical painting, because 3 by 5 is near to the gold cut ratio. The grid-lines have a similar purpose being used like a magnet force field. The optimal visual balance can be obtained by minimizing the overall contour-grid distance, which can be expressed with a single scalar value.

Greenfield in [Gre05] suggested and implemented metrics, which are used to automate the process of guiding image evaluation. The use of the applied metrics and functions is illustrated with an interesting series of images generated by an evolutionary algorithm.

Del Acebo and Sbert [AS05] have introduced Bedford's law to image analysis. The distribution of digits in pixel luminance values of an arbitrary image differs from the Bedford's distribution characterizing random sequences, like in natural images. A normalization of Bedford's values and the given distribution of these values defines a scalar value, which helps in recognizing the naturalness of an image.

3. Computation of Local Contrasts

As stated above our main idea is to compute local contrast factors at various resolutions, and then to build a weighted average in order to get the global contrast factor. The whole method operates in the original image space, we do not transform the image in Fourier or any other space like some other methods do (see Section 2). Furthermore, we have limited our method to the grayscale images only. The color contrast is not simply extrapolated grayscale contrast. Color contrast phenomena is much more complex, and it is out of scope of this paper.

Let us explain how local contrasts at various resolutions are computed now. We will start with the original image, computing the local contrast at the finest resolution. We define the local contrast as the average difference between neighboring pixels. Since we want to build a human perception based method we have to use perceptual, rather then linear luminance. The perceptual luminance can be approximated with the square root of the linear luminance, and according to the sRGB definition the linear luminance is gamma corrected luminance using a gamma of 2.2 for standard displays.

Let us denote the original pixel value with k, $k \in \{0, 1, ..., 254, 255\}$. The first step is to apply gamma correction with $\gamma = 2.2$, and scale the input values to the $[0, 1]$ range. We will denote the scaled and corrected values – linear luminance – with l,

$$l = (\frac{k}{255})^{\gamma} \tag{1}$$

The perceptual luminance L is now

$$L = 100 * \sqrt{l} = 100 * \sqrt{(\frac{k}{255})^{\gamma}} \tag{2}$$

Note that we have used the square root to compute luminance (like in Coloroid [Nem87] or Hunter [Hun92] color systems), instead of CIE L (as in Lab or Luv) cubic root formula, because the view field is wide and we observe simultaneously a lot of different patches, just like in Coloroid or Hunter system conditions. The CIE L formula has been designed for a small field of view and adopted laboratory settings, which differ a lot from our experiment setup.

Once the perceptual luminances are computed we have to compute local contrast. For each pixel we compute the average difference of L between the pixel and four neighboring pixels. Figure 3 shows a pixel L_i and neighboring pixels used to compute local contrast lc_i for pixel i.

Assuming the image is w pixels wide and h pixels high, and the image is organized as a one dimensional array of row-wise sorted pixels, the local contrast lc_i for pixel i is:

$$lc_i = \frac{|L_i - L_{i-1}| + |L_i - L_{i+1}| + |L_i - L_{i-w}| + |L_i - L_{i+w}|}{4} \tag{3}$$

For pixels at the edges only the available neighbouring pixels are taken into account.

The average local contrast for current resolution C_i is computed now as the average local contrast lc_i over the whole image.

$$C_i = \frac{1}{w * h} * \sum_{i=1}^{w*h} lc_i \tag{4}$$

We have to compute the C_i for various resolutions. Once the C_i for original image is computed, we build a smaller resolution image, so that we combine 4 original pixels into

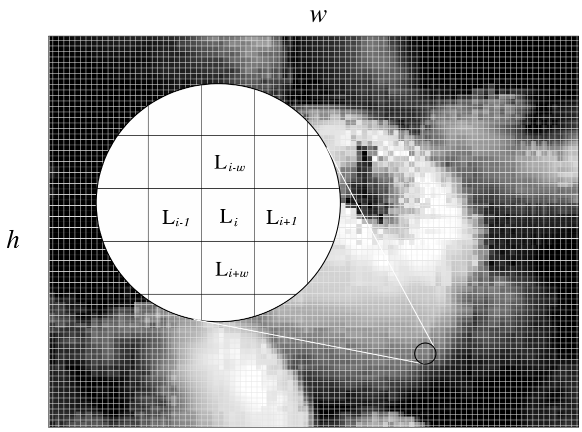

Figure 3: *Local contrasts for each pixels are computed as the average difference between perceptual differences of neighboring pixels.*

one super pixel. The image width is half the original width and the image height is half the original height now. The superpixel value is computed as average linear luminance, and this is than converted to perceptual luminance. The C_i for this resolution can easily be computed and the process continues until we have only few huge superpixels in the image. Let us denominate the number of iterations as N. Figure 4 illustrates the creation of lower resolution images.

Now that we have computed average local contrasts C_i, we need to find weigh factors w_i, which will be used to compute the global contrast factor

$$GCF = \sum_{i=1}^{N} w_i * C_i \tag{5}$$

We have designed an experiment which will help us in finding the weighting factors. Section 4 describes the experiment.

4. Design of the Experiment

The main task in the experiment is sorting of images according to the perceived contrast. At the very start of the experiment every user gets a written description of the task and short explanation how to use the system. Since we have conducted the experiments at different times and places, it was important that all test persons receive exactly the same instructions, especially the formulation of what to evaluate. Once the instructions have been read the system can be started. The system displays four random images from an image database. The user has to order the four images according to the perceived contrast. Then the user has to specify the level of certainty for the ordering. We provided four levels of certainty:

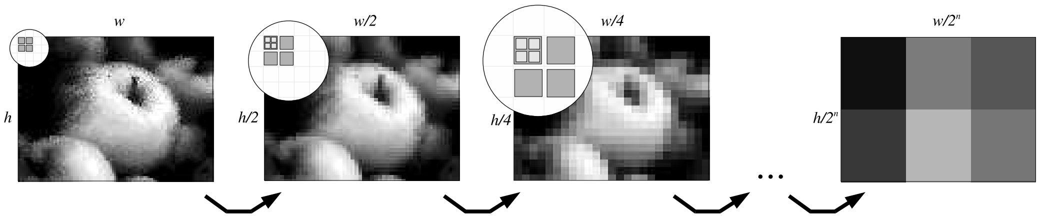

Figure 4: *Creation of super pixels of various resolutions.*

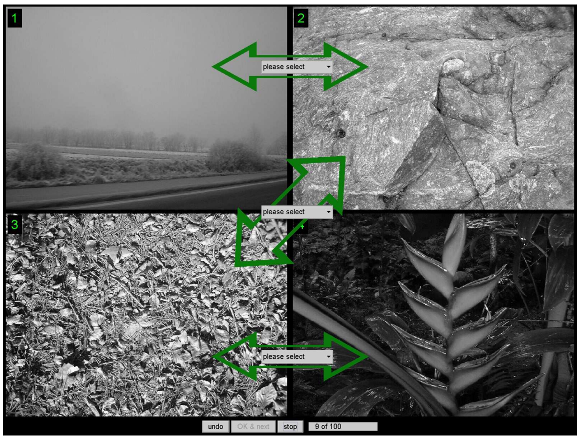

Figure 5: *Application used to conduct user tests*

- undecidable, which means "I think they have the same contrast"
- decidable, which means "I think the ordering is correct"
- very decidable, which means "I am certain that the ordering is correct"
- fixed, which means "It is obvious that the ordering is correct"

After the selection is completed for all four images, a new set of images is displayed. Note that images can appear again, and again, in different contexts (surrounding images). Our goal is to have as many observations as possible. The more comparisons of a particular image there are, the more reliable this method is.

Figure 5 shows a screenshot of our application.

Once the experiment is completed, we can analyze the results. The idea is to extract pair wise comparisons. Only directly compared images will be taken into account. We did not make use of a possible transitivity of the decisions. If for example an user orders images as A < B < C < D, we will use only A < B, B < C, and C < D comparisons. We did not make use of A < C, or A < D, or B < D. Note that e.g. AB combinations can appear in other sets, and that the comparison mark does not have to be the same in the other sets. This

Table 1: *The number of choices for 4 possible rankings*

Decision	Pair count
0 (undecidable)	424
1 (decidable)	1123
2 (very decidable)	1369
3 (fixed)	594

is true for single users, and even more probable across all experiments.

4.1. Experimental Ranking of Images

We have conducted the experiment with 12 users of different ages, gender and professions. The image set consists of 100 images and was kept the same for the whole experiment. We have tried to balance the ratio between the number of images and the number of repetitions of comparisons. Every participant was asked to sort approximately 100 quadruples, which took about 1 hour on average. In total 1170 quadruples were sorted, resulting in 3510 direct, pair-wise comparisons. Some image pairs were compared more than once. It is interesting that different users (and sometimes even the same user) ranked the image pairs differently in different contexts. Some image pairs even had results ranging from A is obviously larger than B to B is obviously larger than A. We wanted to sort all images after the experiment in order to use the sorted list for weighting factor computation (see Equation 5).

We tested various algorithms in order to sort the images, but the closed circles like A > B and B > A in the same time were always problematic. Finally we applied a very simple approach for the partially orderable set. We assigned qualitative categories to the 3, 2, 1, 0, -1, -2, -3 *relation-numbers*. The negative numbers were introduced to represent AB and BA orderings. If a user said that A has *fixed* more contrast than B, the AB pair received 3, and if the user statement was the opposite, the pair received -3. Table 1 shows the distribution of 3510 directly compared pairs in the categories.

Once the values were assigned we computed the average relation number for each image, by summing up all relations and dividing the sum through the number of occurrences.

The maximum average value was 2.35 and the smallest value was -1.30. Figure 6 shows the images with the minimum (left) and the maximum (right) average values in the set.

5. The Weighting Factors

The main idea is to find weighting factors for each resolution so that the computed GCF corresponds to the experimental results as closely as possible.

We have tried different approaches, an early idea was to find a continuous function with a minimal overall quadratic error of differences between the relation numbers and the GCF of a given image pair. Another approach was an *after-ranking* idea, which minimizes the differences between the average value of the non-integer relation number and the GCF values of images.

Finally, we focused at a GCF function, which results in a similar global ranking of images compared to the result of the experiment. The results are convincing. The images in the high and low range have a good overlapping with the observation. The middle part of the list is less precise, causing a shift of up to 30 places in the 100 images set. The reason is obvious. Most contradictory cases were in this range, therefore not even the users could not be sure how to order these images.

5.1. Images Data

Images used in the experiment had the resolution of 800 times 600 pixels. We have chosen this resolution in order to use the most of the 1600 x 1200 monitor space during the experiment. We have computed superpixels of sizes: 2, 4, 8, 16, 25, 50, 100, 200. Of course, we have used the original resolution as well. This gives us 9 different resolution levels. This means that Equation 5 becomes in our case:

$$GCF = \sum_{i=1}^{9} w_i * C_i \qquad (6)$$

The weighting function was searched in form of a second order polynomial function. We generated quasi-random numbers for some free parameters to determine the weight values. With these parameters set, the GCF was computed according to Equation 6 for every image and the images were then sorted according to the GCF value. These results were compared with the already sorted experimental results. The correlation was then simply the average absolute difference of the indices of the two ordered series. The optimum approximation for the weighting factors follows from the best fitting and equals:

$$w_i = (-0.406385 * \frac{i}{9} + 0.334573) * \frac{i}{9} + 0.0877526 \qquad (7)$$

where $i \in \{1, 2, ..., 8, 9\}$

If we would have a significantly larger image set and significantly more userss, we would obtain a more precise GCF.

In order to compare our function with the contrast sensitivity function proposed by Mannos and Sakrison [MS74] we had to define standard viewing conditions. The contrast sensitivity function is defined for cycles per visual degree, so we had to calculate how many pixel-pairs or cycles are within 1 degree. Slightly changing the viewing distance or resolution will not have a great impact on numbers, but we still have to keep view distance and resolution dependencies in mind. The monitor we have used has a horizontal resolution of 1600 pixels and display width of 40 cm; the viewing distance was 60 cm.

Figure 7 shows the Mannos and Sakrison Contrast sensitivity function (CSF) [MS74], and our curve for 9 resolutions. Although the curves are different they share some important characteristics. Both curves start low, have the peak then, and end low again. However, the GCF function is significantly smoother. CSF overestimates the 1-2-3 resolution levels, and underestimates the 5-6-7-8, large super-pixels. The reason for the difference between the two functions is based in the fact that CSF is an analytical approach; it is a result of a sterile, laboratory threshold experiment series. Our method, on the other hand, uses a synthetic approach. We do not use elementary simple luminance patches or sinus patterns, but sort a set of complex and real images under real lighting conditions. The difference of the two approaches is evident. The later approach is not unknown in color theory research, the coloroid system [Nem87] is derived from a set of experiments under real lighting conditions as well.

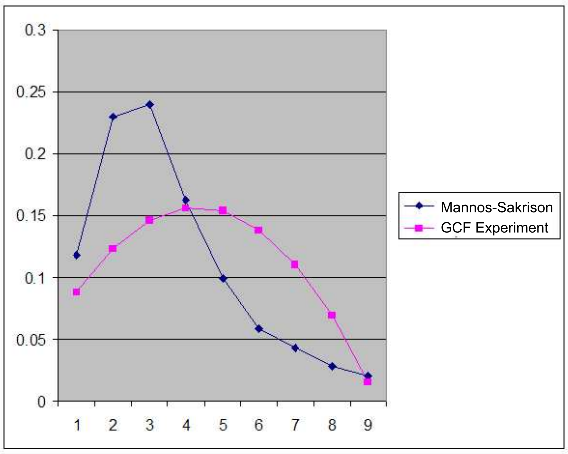

Figure 7: *The original Manos and Sakrison Contrast Sensitivity Function and GCF weight factors for 9 used resolutions. Numbers 1 to 9 correspond to superpixel sizes – 1, 2, 4, 8, 16, 25, 50, 100, and 200 – used in our case.*

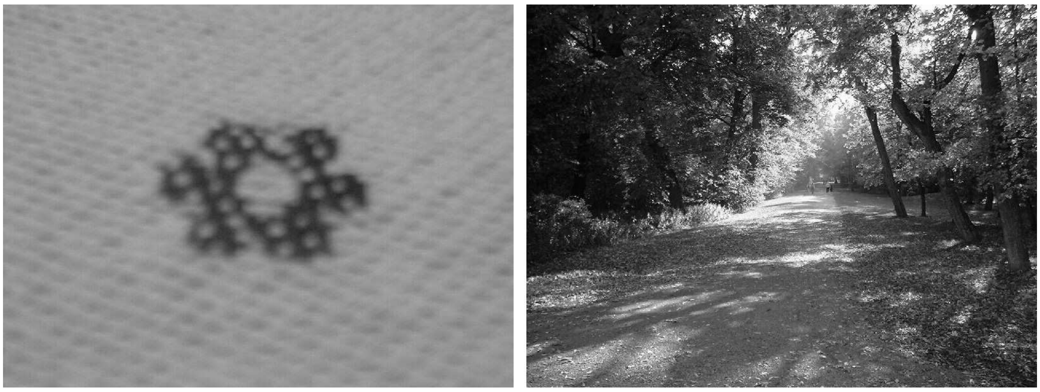

Figure 6: *The least detailed image on the left hand side and the most detailed image on the right hand side according to the first sorting. The GCF reflects the result of observations, too. GCF values are: 1.19 and 5.35*

6. Results

The goal of our research was to find a single scalar value, which characterizes the overall appearance of an image. In particular, it tells us if there are lot of changes in the image at various resolution levels. We call this value *Global Contrast Factor*. It measures the richness of contrast in details and different local contrast effects at all patch-sizes simultaneously.

The proposed method computes the GCF as a weighted average of local contrast factors at various resolutions. We have used 9 resolutions in our experiment.

To illustrate our new GCF, we depict the local contrast factors at 9 resolution levels for the waterfall and moonlight image shown in Figures 1 and 2.

Figures 8 and 9 show the local values for the two images at various resolutions (1, 2, 4, 8, 25 , 50, 100, 200 size super-pixel). Each pixel depicts its local contrast as defined in Equation 3. Dark pixels mean that the difference to neighbors is small. Note that the moonlight image has a lot of dark pixels at low resolutions (second image in the first row of Figure 9) and the waterfall image has much more bright pixels at the same resolution. Note also that a homogeneous gray image would have all pixels black for all resolutions, and a 1 pixel checkerboard image would be white at the highest resolution and black otherwise.

Table 2 shows the values for local contrast factors C_i as defined in Equation 4 for our nine levels and the GCF. The GCF is significantly higher, practically 2 times larger for Figure 1 than for Figure 2, just as expected.

Figure 10 shows three images (from our set) with low, medium and high contrast according to the proposed formula.

7. Conclusions and Future Work

The GCF proposed in this paper is a measure of overall perceived contrast of an image. The proposed solution is based on the experiment where 12 users have tried to sort 1170 quadruples of images. There were many contradictions in the experiment results, but we have succeeded in finding the weighting function which corresponds to the experiment especially good in the high and low contrast areas.

The presented GCF formula seems to be practical and possibly useful in different areas. A higher GCF always indicates more noticeable details which usually results in better image quality. This fact can be used in future applications. E.g. an open issue in volume visualization is how many semi-transparent layers can be perceived and easily understood simultaneously. With well balanced guided reflectance/transparence layer settings the visualization will be more pleasant and the 3D structures will be more easily understandable. A similar parameter optimization problem using the GCF is lighting design. The GCF can help us in selection from a pre-selected light source setup, characterized by geometry, spatial light characteristics and absolute luminance, the spatially most variable or just the most equalized lighting, depending on application area. Content based image retrieval can use the GCF or local contrast factors at different resolution levels as a useful additional tool besides the already used histogram, color and other parameters. The GCF can steer the tone mapping techniques as well. The GCF lead us to an interesting mathematical problem, namely how to generate a picture with the highest possible GCF?

We plan to extend GCF for color images. Finding an appropriate GCF function for color images is a complex issue, since color contrast can not be considered as simple extension of luminance contrast. Furthermore, color harmony plays an important role for color images, and contrast optimization has to be constrained with color harmony issues.

Table 2: *Local contrasts for the waterfall and moonlight images*

	2-pix	4-pix	8-pix	16-pix	25-pix	50-pix	100-pix	200-pix	GCF
Waterfall	0.381086	0.565784	0.664016	0.852208	1.147577	1.194205	1.244527	0.859345	6.908748
Moonlight	0.029743	0.084196	0.191028	0.379645	0.637474	0.708166	0.809912	0.722243	3.562407

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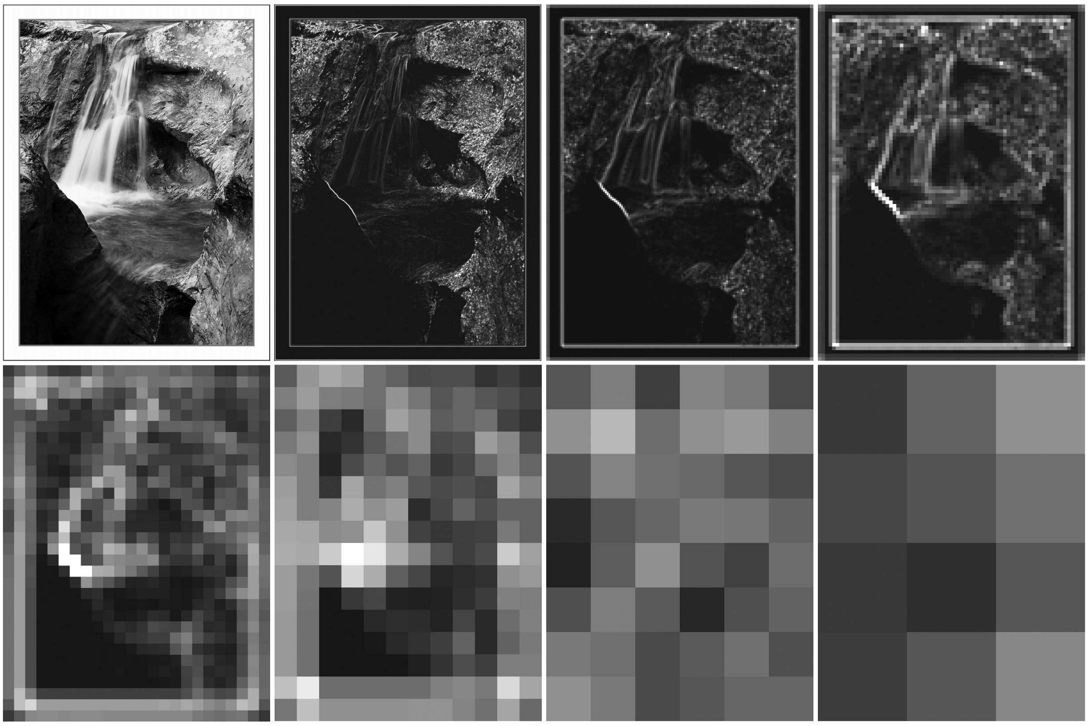

Figure 8: *Series of images depicting local contrasts used to compute global contrast factor for the waterfall image*

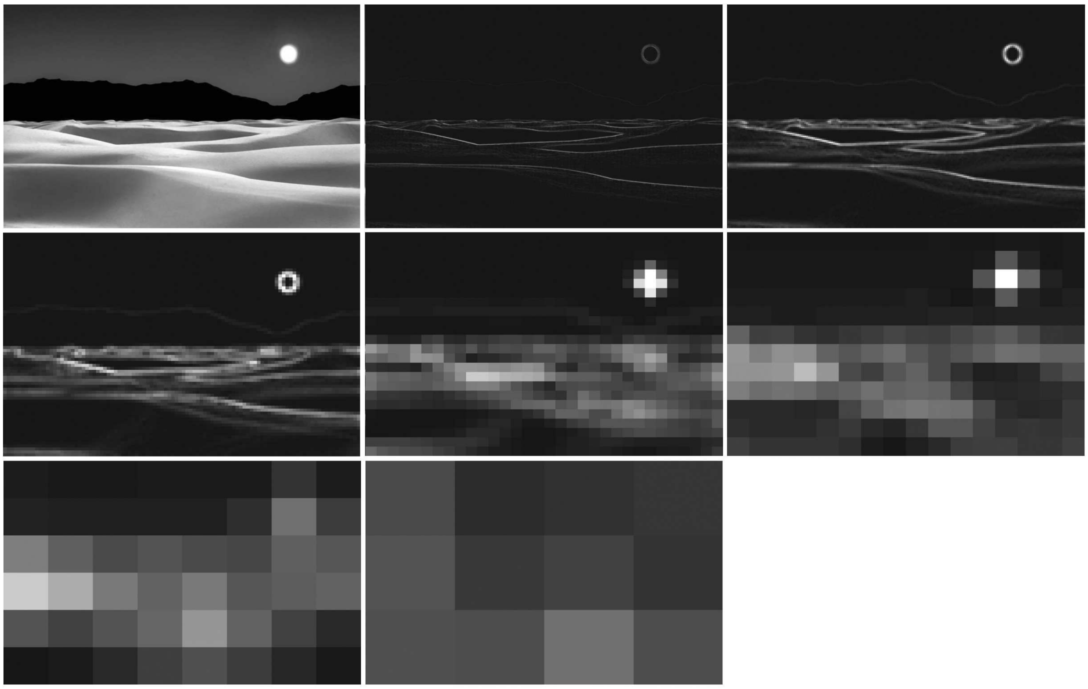

Figure 9: *Series of images depicting local contrasts used to compute global contrast factor for the moonlight image*

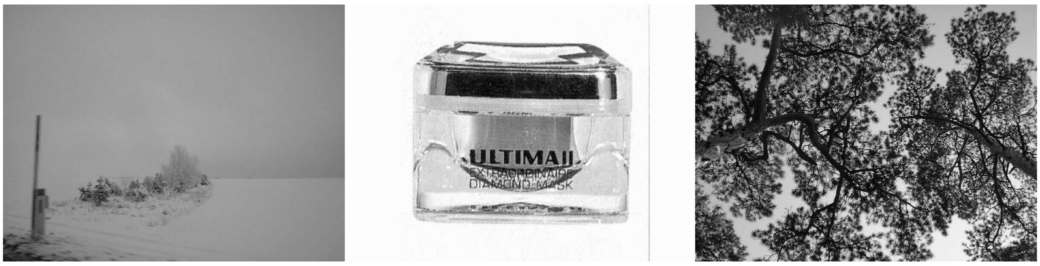

Figure 10: *Three images with increasing GCF, according to the newly proposed formula. The GCF values equal: 0.711936, 3.511858, and 8.493782*