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An Efficient Perception-based Adaptive Color to Gray Transformation

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Abstract

The visualization of color images in gray scale has high practical and theoretical importance. Neither the existing local, gradient based methods, nor the fast global techniques give a satisfying result. We present a new color to grayscale transformation, based on the experimental background of the Coloroid system observations. We regard the color and luminance contrasts as a gradient field and we introduce a new simple, yet very efficient method to solve the inconsistency of the field. Having a consistent gradient field, we obtain the resultant image via fast direct integration. The complexity of the method is linear in the number of pixels, making it fast and suitable for high resolution images.

Categories and Subject Descriptors (according to ACM CCS): I.3.3 [Picture Image Generation]: Display Algorithms, Viewing Algorithms; I.4.3 [Image Processing and Computer Vision]: Enhancement-Filtering

1. Introduction

Nowadays, except for a few artistic and scientific applications, the vast majority of captured images are color photographs. On the other hand, many laser printers are still black-and-white, and most of the pictures in daily newspapers published in the world are predominantly gray-scale images. Thereby the practical importance of color to grayscale transformations is clear. The theoretical challenge is also evident. The color to gray transformation is a mapping of a 3D set with spatial coherences to a one dimensional (1D) space and it necessarily leads to some information loss. What is the best way? Which way gives the highest perceptual equivalence? Does there exist a universal approach?

The solution requires the preservation of chromatic contrasts during the conversion to luminance contrasts and the associated evaluation of the luminance and chrominance changes (gradients) and values. The problem combines various aspects of color vision and spatial vision. How does the visual effect of chrominance and luminance contrasts depend on spatial frequencies?

The above questions do not have simple solutions, as adaptive color to gray transformations are not generally found in nature. We believe that global transformation approaches cannot give a full answer to the above questions, although they appear to offer some fast and acceptable results. The adaptive local methods hold the promise of a much better solution, although they suffer from theoretical problems in perceptual modeling and practical difficulties in numerical calculations. In this paper, we present a perceptually-based adaptive approach using the experimental background of the Coloroid observations. We investigated the relative equivalent luminance differences for a set of chromatic differences at a given spatial frequency, using 10×10 cm solid color samples. However, a comprehensive spatio-chromatic analysis still demands further investigation.

The paper is structured as follows. We review previous work on color to gray image transformation in Section 2. In Section 3, we describe the Coloroid color system and we present our new observations based on the Coloroid. Sec-

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Full color versions of the images and other materials are online: http://www.cgg.cvut.cz/~cadikm/color_to_gray

tion 4 introduces an efficient gradient-based color to gray transformation algorithm powered by a new gradient inconsistency correction method. Then, in Section 5, we show and discuss the results of the presented transformation algorithm. Finally, in Section 6, we conclude and suggest some ideas for future research.

2. Related work

There are several approaches available in the literature that aim to convert color images to grayscale. Strickland et al. [SKM87] proposed a local color image enhancement technique used to sharpen images based on saturation feedback. Zhang and Wandell [ZW96] devised a spatial extension of the CIELab color model (S-CIELab) that is useful for measuring color differences between images. Using the pattern-color separable transformation, the S-CIELab difference measure reflects both spatial and color sensitivity. Bala and Eschbach [BE04] presented spatial color to gray transformation that locally preserves the chrominance edges by introducing high-frequency chrominance information into the luminance channel. The method applies a spatial high-pass filter to the chromatic channels, weighs the output with a luminance dependent term, and finally adds the result to the luminance channel. Grundland and Dodgson [GD05] proposed the decolorize algorithm for contrast enhancing, color to grayscale conversion. The method applies a global color to grayscale conversion by expressing grayscale as a continuous, image dependent, piecewise linear mapping of the RGB color primaries and their color saturation. The authors calibrate the behavior of their method by using three parameters to control contrast enhancement, scale selection, and noise suppression. The authors suggest image independent default values for these parameters. Gooch et al. [GOTG05] presented a Color2Gray algorithm which iteratively adjusts the gray value of each pixel to minimize an objective function based on local contrasts between pixels. The method applies three free parameters (θ, α, μ), but the authors do not provide image independent default values. Moreover, the complexity of the method is $O(N^4)$. Hence, the method is very slow and it is difficult to apply to high resolution images. Rasche et al. [RGW05] presented a color to gray technique that aims to preserve the contrast while maintaining luminance consistency. Authors approach the problem by means of constrained multidimensional scaling which scales badly with the number of colors, and therefore the color quantization is suggested. However, due to the necessary quantization of colors the method produces quantization-like artifacts. Therefore, the usage of this method is very questionable for images with continuous tones (e.g. real-world photos). Moreover, the time-demands are enormous (even a low-res image transformation takes minutes) and depend on the number of colors.

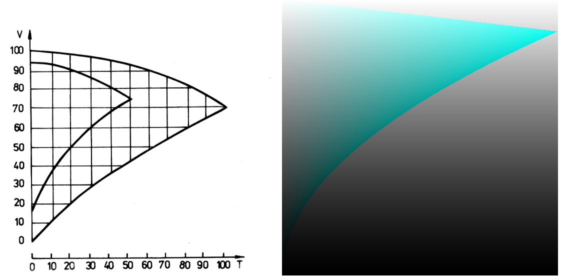

Figure 1: *Left: shape of the Coloroid gamut at a fixed hue value. Right: turquoise hue plane of the Coloroid space.*

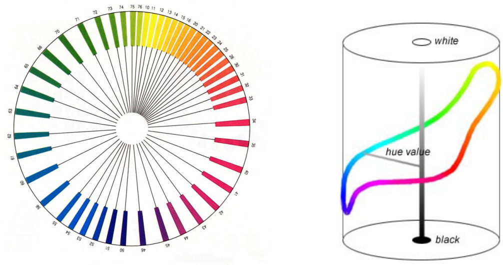

Figure 2: *Left: 48 limit colors of the Coloroid system. Right: curve of Coloroid limit colors in 3D.*

3. The Coloroid system

The Coloroid is a color-order system and color space with conversion formulas to and from CIE XYZ system. The Coloroid system is based on huge number of observations [Nem01] and represents perhaps the most adequate tool or "natural language" to describe harmony relationships and other psychometric attributes between colors [NNN05]. The experimental arrangement of the observations of the color harmony relationships is an ideal tool to study the basic questions of the color to gray transformation, especially to find the chrominance-luminance equivalent attributes on a relative scale.

Conditions of observations and basic concept of the Coloroid system differ from other color order systems. In typical Coloroid experiments, the observer is given a wide field of view to observe a large set of often non-neighboring color samples, and must give their responses relative quickly. These conditions make it similar to an observation of a complex image in the real life. Under these viewing conditions the human vision system can distinguish a reduced number of colors, especially in the darker regions. The colors in Coloroid can be obtained by additive mixture of the black, white and the limit-color, by ratios s, w, and p, respectively, where $s+w+p=1$. The limit-colors were the most saturated *solid-colors* instead of spectral colors. Due to the very great number of observations and also to the obtained good correlations, we consider the basic concepts of Coloroid to be *axioms*, which are valid for the above mentioned view-conditions:

1. Surfaces of a constant Hue (A) form a plane, containing the neutral axis and a hue dependent limit-color, unlike most of the other systems that have curved hue-surfaces (e.g. the Munsell system).
2. Saturation $T = const * ratio(p)$ of the limit-color, where the constant depends on the hue.
3. Lightness $V = 10 * Y^{1/2}$. Unlike the ds line-element based spaces, the Coloroid does not contain a 3rd root or a logarithmic formula here.

Fig. 2 (left) shows the circle of 48 limit-colors, while Fig. 2 (right) shows the continuous 3D limit-color line. Fig. 1 (left) demonstrates the typical shape of the Coloroid gamut at a fixed hue value. The lightness of the most saturated point depends on the hue according to Fig. 2 (right). The two Coloroid gamuts represent two limit-color selections. The larger one corresponds to the spectrum and purple limit-colors and smaller to the most saturated solid-colors, which will be used in our paper. Concepts and formulas of Coloroid can be found in several basic publications [Nem80, Nem87, Hun92], a deep survey of application areas can be found in [Nem04].

3.1. Observations based on Coloroid

After the above short survey we present the experiments in color to gray conversion. First, we studied the relative *luminance difference of the hue pairs* in an average sense. We first selected seven basic colors, one from each Coloroid hue group. For these seven basic colors, Table 1 shows the values of the Coloroid hues A, their characteristic wavelengths λ and their angular degrees φ for the D65 white point in the CIE xy chromacity diagram. The observers' task was to rank the color and gray samples, or to fit missing samples into color series with short adaptation time (semi-adapted eye) [Nem04]. The obtained 7×7 matrix (see Table 2) contains the relative gray-equivalent differences. The matrix has zero diagonal and it is anti-symmetric. The maximal value is scaled to 10. The largest perceived difference is from the A=50 blue hue to the A=10 yellow hue. For arbitrary (A1, A2) saturations, we applied 4 linear interpolations, which preserved the anti-symmetric property of the perceived differences. In the Section 4.1.2, we describe how to generalize the above hue-pair based gray change for arbitrary saturations.

The second observation series aimed to formulate the *gray-equivalence of the saturation increase*. We investigated the effect of the saturation increase for all of the above hues (A=10, 20, 30, 40, 50, 60, 70) at different constant luminance levels (V=45, 65, 85). As above, all of the observations were scaled to maximal value of 10. The unexpected fact is that the equivalent gray difference changes *non-monotonously*! For example, on the A = 60 hue page at the Coloroid-lightness V = 85 in the realistic range of saturations (T) for solid and monitor colors we obtained:

Relative saturation difference	1	2	3	4	5
Relative Δ-gray	1	2	4	0	-5

A	λ	φ
10	570.836	58.040
20	582.640	32.898
30	602.717	5.533
40	-504.836	-46.209
50	450.000	-116.628
60	490.371	-174.503
70	536.295	103.890

Table 1: *Definition of the seven basic Coloroid hues*

A/A	10	20	30	40	50	60	70
10	**0.0**	-2.5	-5.0	-7.0	-10.0	-5.0	-2.0
20	2.5	**0.0**	-2.5	-5.0	-8.0	-3.0	1.5
30	5.0	2.5	**0.0**	-3.0	-5.0	-3.0	3.5
40	7.0	5.0	3.0	**0.0**	-2.5	1.0	4.0
50	10.0	8.0	5.0	2.5	**0.0**	4.0	8.5
60	5.0	3.0	3.0	-1.0	-4.0	**0.0**	3.0
70	2.0	-1.5	-3.5	-4.0	-8.5	-3.0	**0.0**

Table 2: *Relative gray-equivalent differences of the basic hue pairs*

In the above example, low saturation differences lead to positive gray differences while high saturation differences appear to lead to negative gray differences – a highly saturated bright turquoise can be visualized by a gray decrease, while the middle saturated one of nearly the same value requires a gray increase. This relationship holds for the entire gamut. We performed the interpolation between the seven selected hues using the maximal absolute solid-color saturation values of the 48 Coloroid pages. Thereafter, we apply *relative saturations* at every hue and luminance level. The relative saturation is defined to take on the maximal value of 5 at the Coloroid gamut border [Nem04]. The relative saturation is obtained using the Coloroid limit-colors. For an arbitrary color, trilinear interpolation was applied, taking proper account of the zero saturation of the black and white points.

The two gray changes mentioned above are scaled on relative scales, independently. We made dozens of additional observations, where two attributes were changed simultaneously, to calibrate the relative scales to each other using linear regression. For example, here are two color pairs from this set of observations (where Δ-gray is the observed equivalent absolute gray difference):

Δ-gray=-1.0 (A1= 70.0, T1= 15.0, V1= 67.0)
(A2= 24.0, T2= 15.0, V2= 67.0)

Δ-gray=+4.0 (A1= 30.0, T1= 32.0, V1= 47.0)
(A2= 50.0, T2= 32.0, V2= 47.0)

4. Adaptive color to gray transformation

Our adaptive color to gray transformation method consists of three steps. In the first step, we regard the color and luminance contrasts as a gradient field which we construct using formulas described in section 4.1. Then, instead of using a Poisson solver or similar computationally-demanding approach, we correct the gradient field using a newly introduced fast and effective gradient inconsistency correction method based on an orthogonal projection (section 4.2). Finally, we integrate the corrected gradient field and transform the values to the display range to get the resulting image.

4.1. Formulas for building the gradient field

We propose two formulas for construction of the gradient field. The first formula is simple to implement and operates directly on the CIELab color data, while the advanced second one takes the full advantage of the Coloroid color space.

4.1.1. A simple new CIELab based formula

In advance to the Coloroid formula, we studied an extension of Color2Gray method [GOTG05] to avoid the artifacts and to reduce the computational costs. Based on the CIELab values, the mentioned method computes the warm-cold hue transient value multiplied by the chroma and finally modified by a stretched tanh (the "crunch") function to obtain the chrominance. The used signed gray difference is either the chrominance or the luminance value selected according to the max function of their absolute values. However, this approach can result in a strongly non-consistent gradient field, e.g. a large negative value can appear immediately after a large positive one. To "blur" this kind of artifacts the method requires a large neighborhood, and practically the complexity of $O(N^4)$.

To overcome the mentioned shortcomings, we introduce a non-max based, continuous function using the CIELab space. Being the max the $n = +\infty$ power-norm, we use the 3rd power norm, which both preserves somewhat from the max feature, but it is also near to the square-root. Let $A = w_a * a$ and $B = w_b * a$, where w_a and w_b in interval [0.2..0.6] are weight factors to reduce the chrominance-luminance ratio. The equivalent luminance has to be smaller than a CIE color difference value, which can go over 200. Our new formula is as follows:

$$\Delta = \left(\Delta L^3 + \Delta A^3 + \Delta B^3\right)^{1/3}. \quad (1)$$

Formula (1) conveys directly the sign of the Δ gray difference. In the worst "diagonal" colors, the difference from the color difference value - using square-root of a and b - is negligible for the wanted purpose. See one of results of this approach on Figure 3; please note that in contrast to Gooch et al., it takes just a fraction of a second to process this image by our method and the result exhibits more details. The gradient field was corrected with the method described in the paragraph 4.2, using the 1-pixel neighborhood. The above method can be simply extended with 4 weight factors, different for positive and negative a and b (red-green and yellow-blue) channels.

Figure 3: *Comparison of our method using the CIELab formula with the CIE Y equivalent and Gooch et al. Top left: original color image, top right: CIE Y equivalent, bottom left: the result of Gooch et al., bottom right: our adaptive color to gray transformation result.*

4.1.2. The Coloroid based formula

The XYZ color system coordinates to Coloroid coordinates transformation and the Coloroid (ATV) based local gray-change (gradient) formula have central importance in the proposed method. Unfortunately, they cannot be given in a closed form, since they contain tables of observations with the appropriately accurate interpolation rules. Therefore, we describe the structure of the formula and explain the meanings of the terms here.

As the relative gray-equivalency of the *hue changes* is given only for 7 basic hues (by the Tables 1, 2), we apply a bilinear interpolation. In particular, we linearly interpolate the φ values to derive the color hues [Hun92]. For an arbitrary hue-pair (A_1, A_2), we obtain this way a H value in the interval of [-10,10]. The hue-term is additive in this model and it depends sub-linearly on the saturation. In the gradient term, the H occurs with a weight factor of the following form:

$$h(A_1,T_1,A_2,T_2) = w_h \times H(A_1,A_2) \times \sqrt{u(T_{1rel}) \times u(T_{2rel})}, \quad (2)$$

where T_{rel} is the relative saturation scaled to [0,5] for every hue plane and at every luminance level, computed from the maximal solid-color saturation. Equation (2) contains the geometrical mean of the two u-factors, and therefore will be

zero if at least one of the two colors is neutral. The $u(x)$, where $x = 2 \times T_{rel}$, is defined as follows:
$u(x) = 0.5 \times x$, iff $x < 0.5$
$u(x) = \sqrt{x} - 0.5$, otherwise.

The *saturation dependent* gray-equivalent change is more complicated, since it depends on hue and on luminance too. We have to evaluate the relative gray-change of both colors. We made observations for the 7 basic hues (Table 1) using the perceptually uniform Coloroid V values, at the luminance levels of 45, 65 and 85. In the black and white point the change is zero ($V = 0$ and $V = 100$). The suggested gray change of a color (A,T,V) due to the saturation term is scaled also to [-10,10], but with a different weighting. We made additional observations to fit the two different scalings to each other. The effect of growing saturation can result in a positive or negative gray change for a fixed hue and luminance. We use the φ values of the 7 basic hues and the data of the most saturated solid colors [Nem04], that is a version of the 48 limit-colors, and furthermore the above mentioned 5 luminance levels. Let us notate $S(A,T,V)$ the gray-change-effect of the saturation of one color. To compute S, we have to obtain the T_{rel} value first, as in the case of the hue. Then we apply a trilinear interpolation using the neighboring φ, T_{rel}, and V values. For two colors, the signed gray-change can be obtained in the form:

$$S(A_1,T_1,V_1,A_2,T_2,V_2) = w_s \times [S(A_2,T_2,V_2) - S(A_1,T_1,V_1)]. \quad (3)$$

The evident part of the gray gradient is the *luminance difference*, without weighting:

$$dL(L_1,L_2) = L_2 - L_1. \quad (4)$$

The color difference (gradient) is then obtained by adding the luminance (5), the saturation (3) and the hue (2) formulas:

$$\Delta_{1,2} = dL(L_1,L_2) + S(A_1,T_1,V_1,A_2,T_2,V_2) + h(A_1,T_1,A_2,T_2). \quad (5)$$

4.2. Gradient inconsistency correction method

Gradient domain imaging methods generally change the original gradient field of an image, or generate an artificial gradient field from a set of images. The key issue of that approach is the backward transformation – e.g. to find an image having the prescribed gradient field. An exact solution of the problem does not exist in general, there are only best approximations. The set of manipulated artificial gradient vectors is not a conservative consistent gradient field, thereby the appropriate unknown image does not exists, and we cannot obtain it via a 2D integration method.

Which image has the nearest gradient field to the given inconsistent one? This question is behind the existing methods. The well known and widely used multigrid Poisson solver, FFT method, or different iterative methods minimize the sum of elementary quadratic error terms containing the finite difference of unknown pixels and as constant the appropriate given horizontal or vertical gradient values. Perhaps the most efficient and elegant technique is the conjugate gradient method with locally adapted hierarchical basis preconditioning [Sze06].

In this section, we approach the problem of inconsistent gradient field with a new question. *What is the nearest consistent gradient field to an existing non-consistent one?* Having the nearest consistent gradients, the image can be obtained by a simple *two dimensional integration* requiring only one addition per pixel. For the sake of simplicity, we will present here the non multi-resolution basic version with an efficient over-projection.

The unknowns of the classical methods are the pixel luminance values. Our new approach uses two times more unknowns, namely all of X and Y components of each gradient vector (grad). The consistency has a simple pictorial meaning: going around a pixel, the total gradient changes have to be zero, see Figure 4 (left). Thereby, every pixel with 4 of the gradient components defines an equation. The total number of these equations is equal to the number of pixels ($N \times M$). The number of unknown gradient terms is $L = (N-1) \times M + (M-1) \times N$, which is approximately $2 \times N \times M$.

The possible inconsistent gradient terms can be described in the $L \approx N \times M$ dimensional space, while the nearest consistent field is searched in the $N \times M$ dimensional linear subspace of the consistent gradient fields. The metric is simply the Euclidean one, which defines the most natural way of "nearest point". The problem in higher dimension is similar to searching of the nearest point of a line or plane from an outer point in the 3D space. Summing the appropriate set of elementary equations with 4 gradient terms, we can obtain the equation of arbitrary closed curves. On all of these curves, or on all closed "Manhattan-lines" containing vertical and horizontal elementary intervals, the sum of the gradients has to be zero.

We remark an important feature of the new technique: nearly all of gradient methods face the problem of the *contradiction of gradients* on different resolution levels. E.g. in HDRI, Fattal et al. [FLW02] constructed an artificial gradient field in a multi-scale way.However, this approach changes also the larger low dynamic range image parts, which would have to remain invariant. Gooch et al [GOTG05] applied "every pixel to every others" comparison in $O(N^4)$ time to avoid the resolution-contradiction problem for a highly inconsistent gradient field and to obtain a pleasant global appearance. Our new consistency-correction method with the simple 1-neighbor gradients gives the wanted appearance, and solves implicitly the resolution-contradiction problem in a new way.

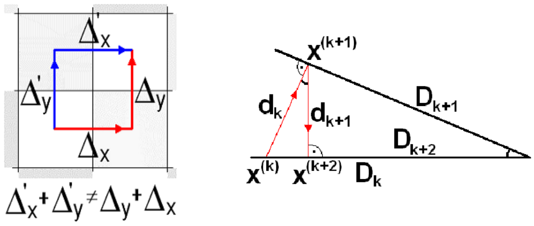

Figure 4: *Left: the sum of gradients around a pixel should be zero, but it is not in the case of inconsistent gradient field. Right: scheme of the orthogonal projection in 2D case.*

4.2.1. The algorithm

To find the nearest point in higher dimensional space, or to project a point orthogonally in a sub-space is generally a time-demanding algorithm. In a lower dimension, the Gram-Schmidt orthogonalization gives a closed form solution. Fortunately, for sparse matrix problems an iterative method tends to the nearest point with very simple elementary projection steps. Figure 4 (left) shows the pixel (middle point) and two different ways around the pixel. The total changes on these two ways have to be the same. After image manipulation or for artificially prescribed gradient field this consistency does not hold. The sum of gradients (E) on the closed curve containing the blue and red parts has to be zero. If it is non-zero, but $|E| > \varepsilon$, we have to change the values for all of closed "1-pixel-ways", until all of E-values converge to zero. In the app. $2 \times N \times M$ dimensional space of gradient components all of the 1-pixel-ways define an equation ($N \times M$), containing only 4 non-zero coefficients:
$g_x(i,j) + g_y(i+1,j) - g_y(i,j) - g_x(i,j+1) = E \neq 0$,
$\mathbf{N} = (0,..,0,+1,+1,-1,-1,0,..,0)$,

$$\mathbf{g}_{new} = \mathbf{g} - 1/4 \times E \times \mathbf{N},$$

(see Algorithm 1), where **g** is the vector describing the whole gradient field. The orthogonal projection method converges to the nearest point of a sub-space, in our case one of the consistent gradient fields. This subspace is the common part of all hyper-planes defined by the 1-pixel-way equations. If we select the equation with maximal error, and project the current gradients in the direction of **N** normal until reaching this plane, or fulfilling the equation, we go nearer to the wanted point according to the Figure 4 (right). The new distance D_{k+1} can be expressed with the old one and with the d_k distance of the projection characterizing the local inconsistency:

$$D_{k+1}^2 = D_k^2 - d_k^2.$$

With maximum error (E) selection, the method is more efficient, than with a cyclical correction of all of pixels, but this latter does not require a structure, e.g. to build a Fibonacci-heap to the quick max selection. On the other hand, the over-projection (e.g. parameter ω in Alg. 1), which is less efficient locally, significantly increases the overall convergence also in the non-multiresolution form of Algorithm 1 (the value of $\omega = 1.8$ is convenient for most images, while for $\omega = 1$ we get the original convergence rate).

Algorithm 1 Inconsistency correction

```
correct (gradient_field grad, double ω, double ε) {
repeat
  max_err=0;
  for y = 1 to YRES-1 do
    for x = 1 to XRES-1 do
      err=grad.X[x][y]+grad.Y[x+1][y]-
         -grad.Y[x][y]-grad.X[x][y+1]
      if |err|>max_err then
        max_err=|err|;
      end if
      s = 1/4 × err × ω;
      grad.X[x][y]=-s + grad.X[x][y];
      grad.Y[x+1][y]=-s + grad.Y[x+1][y];
      grad.Y[x][y]=s + grad.Y[x][y];
      grad.X[x][y+1]=s + grad.X[x][y+1];
    end for
  end for
until max_err < ε
}
```

Having the consistent gradient field, the final image is constructed via simple 2D integration, as shown in Algorithm 2. We believe the reader can implement this new simple, but efficient method very easily.

Algorithm 2 Double integration

```
integrate (gradient_field grad, output_image out) {
out[1][1] = 0;
for y = 1 to YRES do
  if y>1 then
    out[1][y] = out[1][y-1] + grad.Y[1][y-1];
  end if
  for x = 2 to XRES do
    out[x][y] = out[x-1][y] + grad.X[x-1][y];
  end for
end for
}
```

5. Results and discussion

We demonstrate the performance of our new color to gray transformation on a variety of color images and photographs. Figure 5 illustrates the mandatory color to gray transformation test containing largely isoluminant colors. We can observe from this figure how the classical approach results in a constant luminance (see Figure 5 - center). On the contrary, our approach (see Figure 5 - right) transforms the chrominance difference into well noticeable luminance differences.

The low contrast is due to the small visible differences in the original color image, preserving the overall appearance.

Figure 6 exhibits how, beyond other changes, the bluish image parts of the color image obtain a more realistic darker appearance in the resulting graylevel image after applying the proposed adaptive method. On the other hand, Figure 7 (top row) presents an obvious improvement of the final appearance in the details and visibility of the sky area. The sun is well visible in our result, while it nearly disappears in the classical gray conversion. Further examples are illustrated in Figure 7 and in color plates.

The processing time of a color to gray transformation using our approach is in the order of seconds even for high-res images (appr. 5 - 10 seconds per Megapixel), an appropriate value of parameter ε (see Alg. 1) is 0.001 for most images. We are currently working on the accelerated real-time version applying the multi-scale solution.

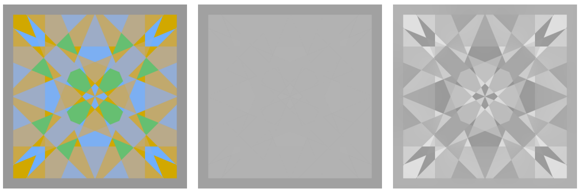

Figure 5: *An artificial isoluminant image. Left: original color image, middle: CIE Y equivalent, right: our adaptive color to gray transformation result.*

6. Conclusions and future work

We presented a new fast and efficient perceptual color to gray transformation method, based on a large number of experiments and observations of the local luminance-chrominance equivalency. Our method describes the luminance-equivalent nature of the whole gamut in a gradient domain, which (as we observed) often has an unexpected behavior with smooth changes. We propose two different formulas for the construction of the gradient field, first one operating in the CIELab color space, while the advanced second one takes the full advantage of the Coloroid color space.

Figure 6: *Left: original color image, middle: CIE Y equivalent, right: our adaptive color to gray transformation result.*

Moreover, we introduced a new gradient inconsistency correction method for solving the gradient field translated problem. The method has a linear complexity in the number of pixels and thereby it is suitable also for high resolution images. The method finds the most natural solution for a given inconsistent gradient field, e.g. the nearest one in the linear subspace of consistent gradient fields. The final image is then obtained via simple and fast 2D integration and clipping of the values.

In the future, we will systematically assess the algorithm performance and we will provide more extensive experimentation including subjective testing (the best transformation requires judgment of photographers and painters). Moreover, we will involve the multiscale processing to make the proposed method real-time.

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References

[BE04] BALA R., ESCHBACH R.: Spatial color-to-grayscale transform preserving chrominance edge information. In *Color Imaging Conference* (2004), pp. 82–86.

[FLW02] FATTAL R., LISCHINSKI D., WERMAN M.: Gradient domain high dynamic range compression. In *Proceedings of the 29th annual conference on Computer graphics and interactive techniques* (2002), ACM Press, pp. 249–256.

[GD05] GRUNDLAND M., DODGSON N. A.: *The Decolorize Algorithm for Contrast Enhancing, Color to Grayscale Conversion*. Tech. Rep. UCAM-CL-TR-649, University of Cambridge, 2005.

[GOTG05] GOOCH A. A., OLSEN S. C., TUMBLIN J., GOOCH B.: Color2gray: salience-preserving color removal. *ACM Trans. Graph. 24*, 3 (2005), 634–639.

[Hun92] HUNT R. W. G.: *Measuring Colour*, 2nd ed. Ellis Horwood Series in Applied Science and Industrial Technology, 1992.

[Nem80] NEMCSICS A.: Coloroid Color System. *Color Research and Application 5* (1980), 113– 120.

[Nem87] NEMCSICS A.: Color space of the coloroid color system. *Color Research and Application 12* (1987), 135– 146.

[Nem01] NEMCSICS A.: Recent experiments investigating the harmony interval based colour space of the coloroid colour system. In *AIC 9th Congress Rochester* (2001).

[Nem04] NEMCSICS A.: *Colour Dynamics, Environmental Colour Design*, 2nd ed. Akadémiai Kiadó, Budapest, 2004.

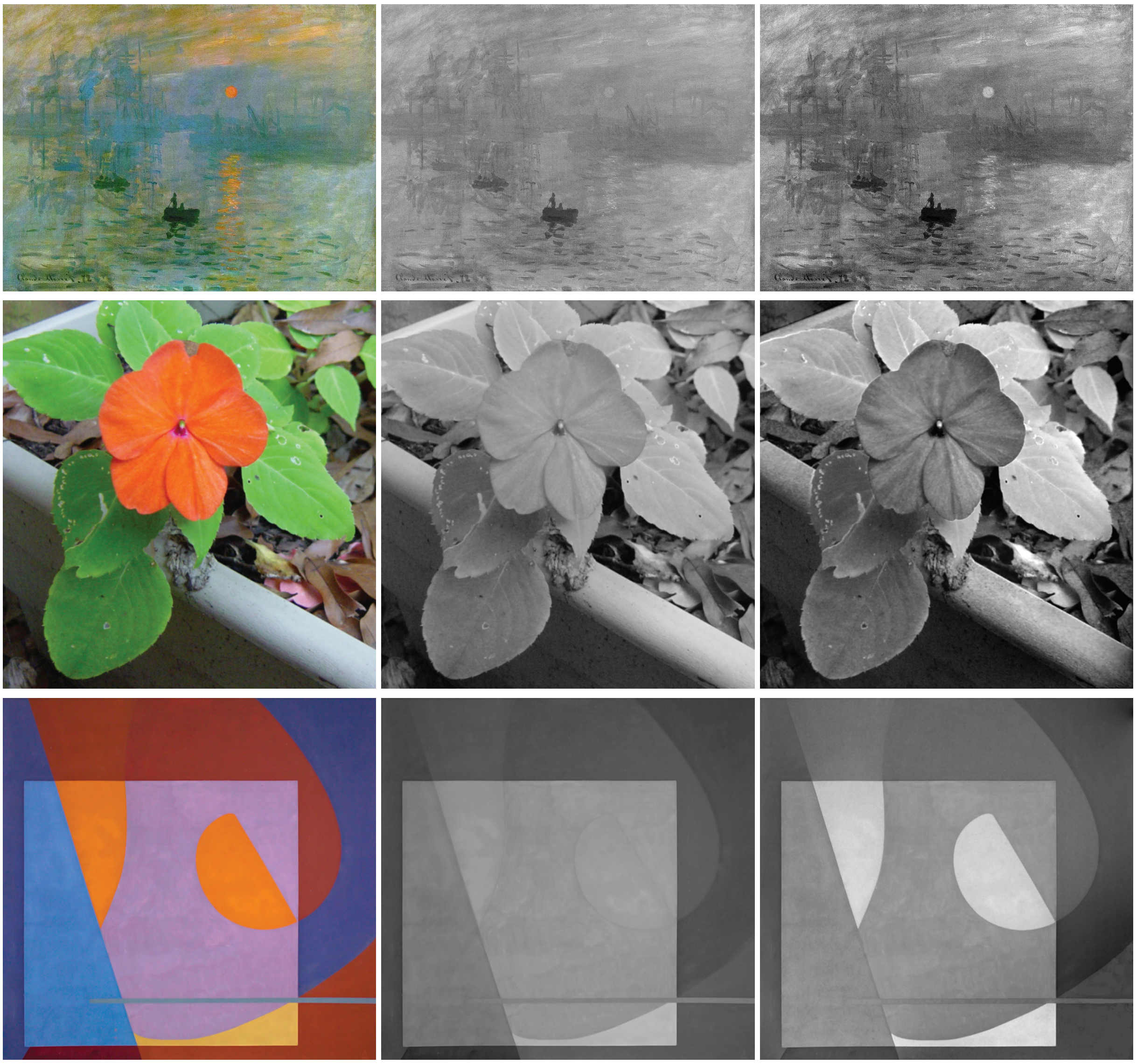

Figure 7: *Left column: original color image, middle column: CIE Y equivalent, right column: our adaptive color to gray transformation result.*

[NNN05] NEUMANN L., NEMCSICS A., NEUMANN A.: Computational color harmony based on coloroid system. In *Computational Aesthetics in Graphics, Visualization and Imaging 2005* (2005), Neumann L., Sbert M., Gooch B., Purgathofer W., (Eds.), pp. 231– 240.

[RGW05] RASCHE K., GEIST R., WESTALL J.: Re-coloring Images for Gamuts of Lower Dimension. *Computer Graphics Forum 24*, 3 (2005), 423–432.

[SKM87] STRICKLAND R. N., KIM C.-S., MCDONNELL W. F.: Digital color image enhancement based on the saturation component. *Optical Engineering 26* (July 1987), 609–616.

[Sze06] SZELISKI R.: Locally adapted hierarchical basis preconditioning. In *SIGGRAPH '06: ACM SIGGRAPH 2006 Papers* (New York, NY, USA, 2006), ACM Press, pp. 1135–1143.

[ZW96] ZHANG X., WANDELL B.: A spatial extension of cielab for digital color image reproduction. In *Proc. Soc. Inform. Display 96 Digest* (San Diego, 1996), pp. 731– 734.