Spatio-Temporal Retinex-like Envelope with Total Variation

Gabriele Simone and Ivar Farup
Gjøvik University College; Gjøvik, Norway.

Abstract

Many algorithms for spatial color correction of digital images have been proposed in the past. Some of the most recently developed algorithms use stochastic sampling of the image in order to obtain maximum and minimum envelope functions. The envelopes are in turn used to guide the color adjustment of the entire image. In this paper, we propose to use a variational method instead of the stochastic sampling to compute the envelopes. A numerical scheme for solving the variational equations is outlined, and we conclude that the variational approach is computationally more efficient than using stochastic sampling. A perceptual experiment with 20 observers and 13 images is carried out in order to evaluate the quality of the resulting images with the two approaches. There is no significant difference between the variational approach and the stochastic sampling when it comes to overall image quality as judged by the observers. However, the observed level of noise in the images is significantly reduced by the variational approach.

Introduction

A great amount of research has been done on Human Visual System (HVS), which is quite difficult to mimick as the HVS has complex and robust mechanisms to acquire useful informations from the physical environment. In particular the color of an area in a visual scene is heavily influenced by the chromatic content of the other areas of the scene. This psychophysiological phenomenon is known as locality of color perception.

One of the earliest models able to deal with locality of perception is Retinex, proposed by Land and McCann in 1971 [14], which is an image processing method that exhibits some behaviors similar to the HVS. The scientific community has continued to be interested in this model and its various applications, as reported in [17, 16]. In the basic Land and McCann implementation of Retinex, locality is achieved by long paths scanning across images. Different implementations and analysis followed after this first work. These can be divided into two major groups, and they differ in the way they achieve locality. The first group explore the image using paths or computing ratios with neighbors in a multilevel framework [7, 13, 15, 21, 8, 4]. and recent approaches work using in particular Brownian motions models [6, 18]. The second group computes values over the image with convolution mask or weighting distances [11, 1, 10, 5, 20].

A recent implementation, constructed to investigate the effects of different spatial samplings, replaces paths with random sprays, i.e. two-dimensional point distributions across the image, hence the name "Random Spray Retinex" (RSR) [19]. In a follow-up, Kolås et al. [12] developed the "Spatio-Temporal Retinex-like Envelope with Stochastic Sampling" (STRESS) framework, where the random sprays are used to calculate two envelope functions representing the local reference black and white points. Both algorithms need a high density of samples in order to lower the amount of noise, but they never sample the whole image in order to keep a local effect. Furthermore the number of sampling points needed increases drastically when increasing the image size and consequently also the computational time.

In this work, we propose and test an alternative method for calculating the two envelope functions of STRESS, replacing the the stochasting sampling with a constrained total variation method. We want to emphasize that although much of idea is the same, it is not just another implementation of STRESS as the two algorithms follow a different strategy for calculating the envelopes and they show different behaviors.

In order to give to the reader a complete and detailed overview, STRESS will be described in the next section, followed by our new proposal. Afterwards, a description of the method of evaluation of our proposal in addition to some implementation details are presented. Finally, experimental results are shown and conclusions are drawn.

The STRESS Algorithm

The STRESS (Spatio-Temporal Retinex-like Envelope with Stochastic Sampling) algorithm developed by Kolås et al. [12] aims to reproduce some of the adjustment mechanisms typical for the Human Visual System. The central part of the STRESS algorithm is to calculate, for each pixel, the local reference black and white points in each chromatic channel. This is done through calculating two envelope functions, the maximum and minimum envelopes, containing the image signal. The two envelopes, denoted as $E_{\max}$ and $E_{\min}$, are slowly varying functions, such that the image signal is always in between the envelopes or equal to one of them. In particular the two envelopes should have the following characteristics: 1) following the signal; 2) being smooth; 3) being edge preserving; 4) touching the global maximum of the image for $E_{\max}$, while the global minimum for $E_{\min}$.

For each pixel p_0, the two envelopes are estimated using a random spray modeled as follows:

$$E_{\min} = p_0 - \overline{v}\,\overline{r}, \tag{1a}$$

$$E_{\max} = p_0 + (1 - \overline{v}\,\overline{r}) = E_{\min} + \overline{r} \tag{1b}$$

where:

$$\overline{r} = \frac{1}{N} \sum_{i=1}^{N} r_i, \tag{2a}$$

$$\overline{v} = \frac{1}{N} \sum_{i=1}^{N} v_i \tag{2b}$$

N denotes the number of iterations, while r_i is the range of the samples and v_i the relative value of the center pixel given as:

$$r_i = s_i^{\max} - s_i^{\min}, \tag{3a}$$

$$v_i = \begin{cases} \frac{1}{2} & \text{if } r_i = 0 \\ \frac{p_0 - s_i^{\min}}{r_i} & \text{else} \end{cases} \tag{3b}$$

$s_i^{\max}$ and $s_i^{\min}$ are the maximum and minimum samples, found as:

$$s_i^{\max} = \begin{array}{c} \max \ p_j \\ j \in \{1, 2, ..., M\} \end{array} , \qquad (4a)$$

$$s_i^{\min} = \begin{array}{c} \min \ p_j \\ j \in \{1, 2, ..., M\} \end{array} \qquad (4b)$$

where M is the number of samples and p_i is the pixel at iteration i.

Given the two envelopes, each pixel p_0 is adjusted as follows:

$$p_{stress} = \frac{p_0 - E_{\min}}{E_{\max} - E_{\min}} \qquad (5)$$

In this way STRESS aims to enhance the contrast of the image, giving highlight/emphasis to details and balance the three channels of the image, thus performing a color correction.

Our Proposal: The STRETV Algorithm

The main feature of the STRESS algorithm is the calculation of the envelopes $E_{\max}$ and $E_{\min}$ for each channel. In our proposal the stochastic sample is replaced with the total variation method for calculating the two envelopes. The following equation describes our model, called *STRETV* (Spatio-Temporal Retinex-like Envelope with Total Variation):

$$\text{minimize} \, TV = \text{minimize} \int_{\Omega} | \nabla E | \, d\Omega + \frac{\lambda}{2} \int_{\Omega} | E - I |^2 \, d\Omega \quad (6)$$

where I is the original image channel, E is the maximum or minimum envelope, Ω is the domain of the image, $\int_{\Omega} | \nabla E | \, d\Omega$ is the total variational term, and $\frac{\lambda}{2} \int_{\Omega} | E - I |^2 \, d\Omega$ is the non-smooth fidelity term with λ weighting factor for the data attachment.

This minimization is subject to the three following constraints: following the signal, $E_{\max} \geq I$ and $E_{\min} \leq I$. The corresponding Euler-Lagrange equation is as follows:

$$\nabla \cdot \left(\frac{\nabla E}{\| \nabla E \|} \right) - \lambda (E - I) = 0 \qquad (7)$$

where I is the original image channel, E is the maximum and minimum envelope, $\nabla \cdot \left(\frac{\nabla E}{\| \nabla E \|} \right)$ is the driving force to the smoothness, and $\lambda(E - I)$ is the driving force to the data attachment with $0 < \lambda \ll 1$.

The solution is computed using an Euler explicit time marching scheme for each color channel:

$$\nabla \cdot \left(\frac{\nabla E}{\| \nabla E \|} \right) - \lambda (E - I) = \frac{\partial E}{\partial t} \qquad (8)$$

applying Neumann boundary conditions and the regularization proposed by Blomgren and Chan [2] at each iteration. At end of each iteration the constraints are enforced in order to avoid numerical errors.

Results

Preliminary tests indicate that STRETV works well with $\lambda = 0.1$ and $\lambda = 0.001$, using a unit time step ($\Delta t = 1$). The algorithm has been implemented in Matlab (using Parallel Computing Toolbox) and tested on a DELL Latitude Model E6520.

In order to evaluate the quality of STRETV, two perceptual experiments have been carried out. A set of 13 images chosen following the recommendations from [9, 3] were evaluated in a pairwise comparison on neutral grey background to a total of 20 observers. In the first perceptual experiment each STRETV image was compared to its original and the observers were asked to choose the image based on their preference. In the second perceptual experiment each STRETV image was compared to its relative processed with STRESS and in a first round the observers were asked to choose the image based on their preference while in a second round they were asked to pick the image with more noise. Whenever the STRETV image did not succeed in the first experiment, it was discarded from the second experiment.

Figure 1-2 shows the 13 original images in the middle, the corresponding processed by STRETV on the right and the corresponding processed by STRESS on the left. Due to page limitations, it is not possible to analyze all the images but particular interesting results for STRETV can be found in Figures 1(c), 2(l), 2(r) where the reflections present in the water, windows and eyeglasses respectively are more visible and in Figure 2(o) where the red component is corrected and identification of objects in the map are perceptually easier.

Figure 3 shows the preference of the 20 observers on the tested images for the first psychophysical experiment and we can clearly see that STRETV succeeds on 11 of 13 images with six of them with a preference equal or greater than 85% of the rates. The reason of the defeat for Figure 1(i) and of the draw for Figure 2(f) with respect to their original can be found in the fact that observers perceived a loss of naturalness.

Figure 4 shows the preference of the 20 observers for the second psychophysical experiment, where STRETV was compared to STRESS. Figure 5 shows the perceived noise of the 20 observers for STRETV and STRESS. STRETV is preferred for 7 of the 11 images and it results to be less noisy for 9 of the 11 images.

Furthermore, STRETV has lower computational complexity than STRESS, $O(N \cdot n)$ against $O(N \cdot M \cdot n)$, where N is the number of iterations, n is the number of pixels in the image and M is the number of samples. As consequence STRETV is faster than STRESS implemented in MATLAB. On the other hand a new implementation of STRESS in CUDA provided by the original authors [12] is more efficient than STRETV.

A sign-test at 95% confident interval shows that STRETV is significantly better than the original and having the same performance of STRESS but producing images less noisy.

Conclusions

We have developed a new Retinex algorithm called STRETV (Spatio-Temporal Retinex-like Envelope with Total Variation), following the approach of Kolås et al. [12] for the STRESS algorithm (Spatio-Temporal Retinex-like Envelope with Stochastic Sampling), which adjusts each pixel calculating the local reference of lighter and darker points in each channel. This is done estimating two envelope functions, the maximum and minimum envelopes, containing the image signal, through the total variation method.

STRETV shows promising results in contrast enhancement and automatic color correction. A first psychophysical experiment on 13 images with 20 observers confirm the efficiency of the method with a noticeable success of STRETV on 11 images in comparison to the original. A second psychophysical experiment shows that the overall performance of STRESS is not significantly different at 95% confidence level. At the same time a higher preference of the observers of STRETV with respect to STRESS is noticed due to a lower perception of noise.

Future work can consist of extending STRETV to high dynamic range imaging rendering and color-to-grey conversion to

(a)   (b)   (c)

(d)   (e)   (f)
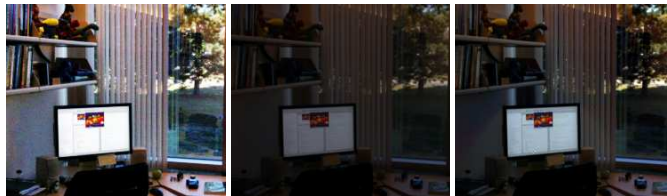
(g)   (h)   (i)

(j)   (k)   (l)

(m)   (n)   (o)

(p)   (q)   (r)

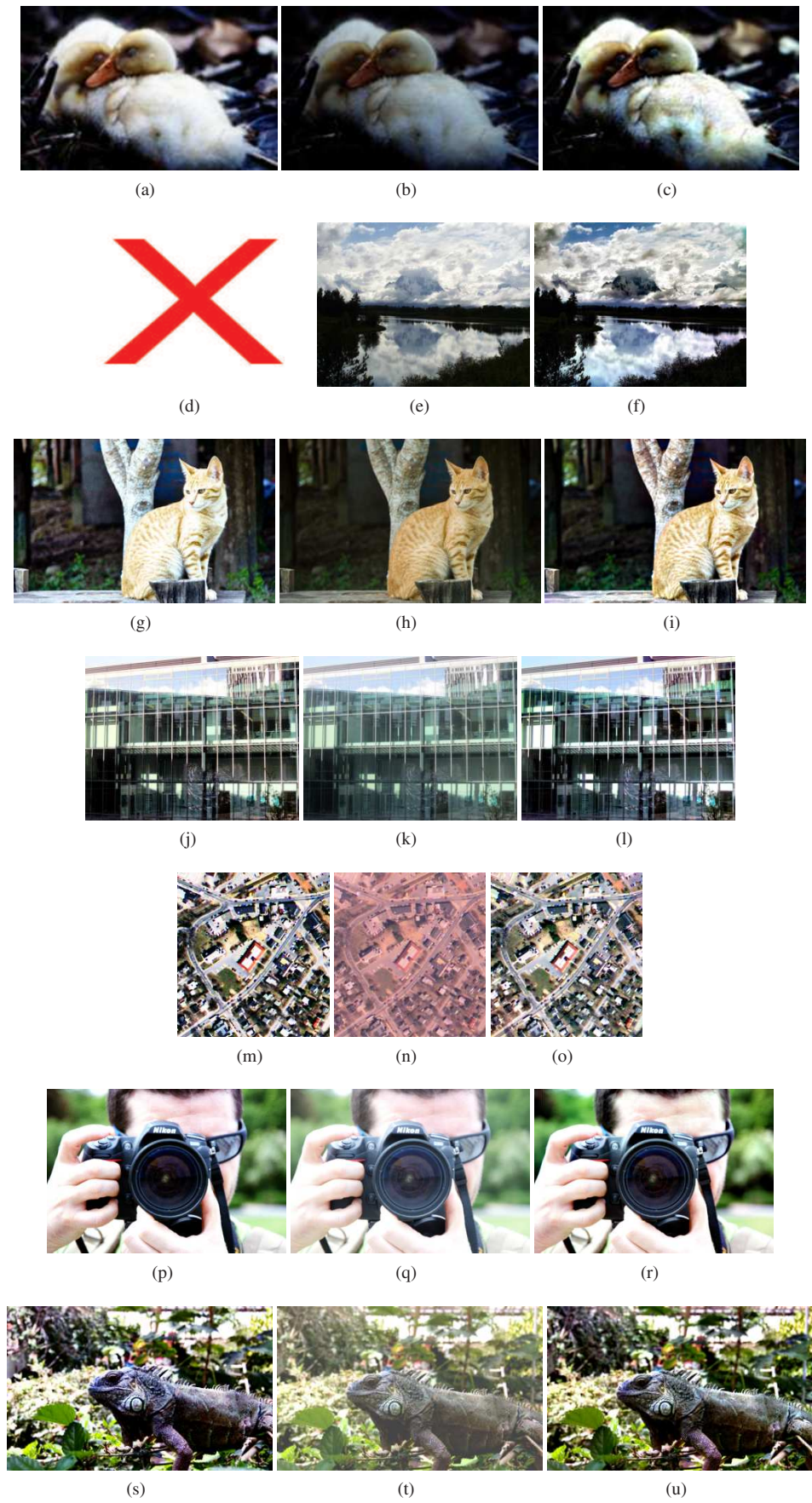**Figure 1.** *STRESS on the left, original in the middle, STRETV on the right.*

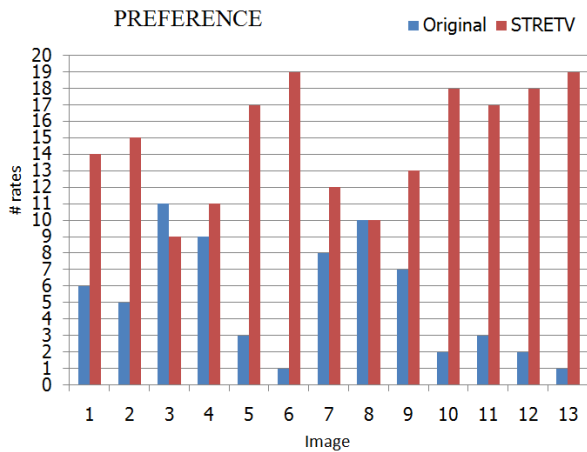**Figure 2.** *STRESS on the left, original in the middle, STRETV on the right.*

Figure 3. *Observer's preference of STRETV with respect to its original on the 13 tested images.*
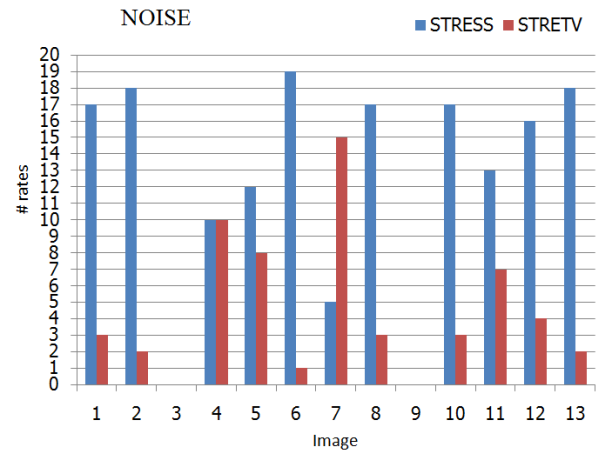

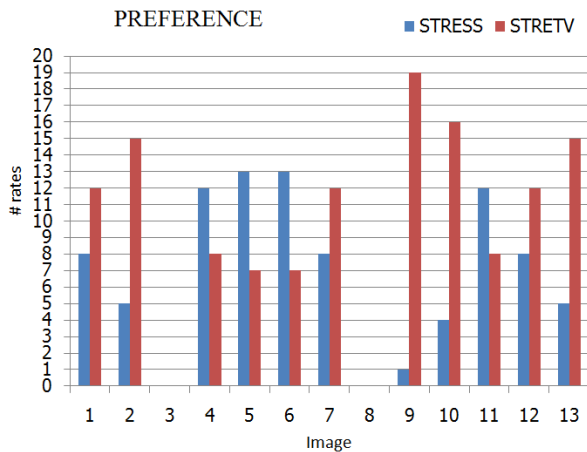**Figure 5.** *Observer's perceived noise of STRETV and STRESS on the 11 tested images.*

Figure 4. *Observer's preference of STRETV in respect of STRESS on the 11 tested images.*

be fully comparable with the STRESS and other spatial color algorithms.

Acknowledgment

References

[1] K. Barnard and B. Funt. Investigations into multi-scale Retinex. In *Color Imaging in Multimedia*, pages 9–17. Technology, Wiley, 1998.

[2] P. Blomgren and T. F. Chan. Color TV: Total variation methods for restoration of vector-valued images. *IEEE Transactions on Image Processing*, (7):304–309, 1998.

[3] CIE. Guidelines for the evaluation of gamut mapping algorithms. Technical Report ISBN: 3-901-906-26-6, CIE TC8-08, 156:2004.

[4] T. J. Cooper and F. A. Baqai. Analysis and extensions of the frankle-mccann Retinex algorithm. *Journal of Electronic Imaging*, 13(1):85–92, 2004.

[5] J. D. Cowan and P. C. Bressloff. *Visual cortex and the Retinex algorithm*, volume SPIE-4662, pages 278–285. The International Society for Optical Engineering, 2002.

[6] G. Finlayson, S. Hordley, and M. Drew. Removing shadows from images using Retinex. In *The Tenth Color Imaging Conference: Color Science and Engineering Systems, Technologies, Applications*, pages 73–79, Scottsdale, AZ, USA, November 2002. IS&T/SID.

[7] J. Frankle and J. McCann. Method and apparatus for lightness imaging. United States Patent No. 4,384,336, 1983.

[8] B. Funt, F. Ciurea, and J. J. McCann. Retinex in MATLAB. *Journal of Electronic Imaging*, 13(1):48–57, January 2004.

[9] J. Holm, I. Tastl, and T. Johnson. Definition & use of the iso 12640-3 reference color gamut. In *Fourteenth Color Imaging Conference: Color Science and Engineering Systems, Technologies, Applications*, pages 62–68, Scottsdale, AZ, 2006. IS&T/SID.

[10] F. O. Huck, C. L. Fales, R. E. Davis, and R. Alter-Gartenberg. Visual communication with Retinex coding. *Applied Optics*, 39(11):1711–1730, 2000.

[11] D. J. Jobson, Z. Rahman, and G. A. Woodell. Properties and performance of a center/surround Retinex. *IEEE Transactions on Image Processing*, 6(3):451–462, 1997.

[12] Ø. Kolås, I. Farup, and A. Rizzi. STRESS: A framework for spatial color algorithms. *Journal of Imaging Science and Technology*, 55(4):040503, 2011.

[13] E. H. Land. The Retinex theory of color vision. *Scientific American*, 237:108–128, 1977.

[14] E. H. Land and J. J. McCann. Lightness and Retinex theory. *Journal of the Optical Society of America*, 61(1):1–11, jan 1971.

[15] D. Marini and A. Rizzi. A computational approach to color adaptation effects. *Image and Vision Computing*, 18:1005–1014, 2000.

[16] J. McCann and A. Rizzi. *The Art and Science of HDR Imaging*. John Wiley, 2011. ISBN: 978-0-470-66622-7.

[17] J. J. McCann. Guest editorial: Special section on Retinex at 40. *Journal of Electronic Imaging*, 13(1):6–7, 2004.

[18] R. Montagna and G. D. Finlayson. Constrained pseudo-brownian motion and its application to image enhancement. *Journal of the Optical Society of America A*, 28(8):1677–1688, August 2011.

[19] E. Provenzi, M. Fierro, A. Rizzi, L. D. Carli, D. Gadia, and D. Marini. Random spray Retinex: A new Retinex implementation to investigate the local properties of the model.

IEEE Transactions on Image Processing, 16(1):162–171, January 2007.

[20] Z. Rahman and G. A. Woodell. Retinex processing for automatic image enhancement. *Journal of Electronic Imaging*, 13:100–110, 2004.

[21] A. Rizzi, D. Marini, and L. D. Carli. LUT and multilevel brownian Retinex colour correction. *Machine Graphics & Vision*, 11(1):153–169, 2002.

Author Biography

Gabriele Simone received his BiT in 2005, and his MSIT in 2007 both at University of Milan - Department of Information Technology, Italy. He is currently pursuing a PhD in Color Imaging. He is a member of the Norwegian Color Research Laboratory at Gjøvik University College and his main research topic is contrast measure, image difference metrics, and tone mapping algorithms in HDR images.

Ivar Farup received the M.Sc. degree in physics from the Norwegian University of Science and Technology, Trondheim, Norway, in 1994, and the Ph.D. degree in applied mathematics from the University of Oslo, Oslo, Norway, in 2000. Since 2000, he has been an Associate Professor at Gjøvik University College, Gjøvik, Norway, mainly focusing on color imaging.