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Nonlinear image sharpening in the HSV color space

Abstract. *This paper presents a concept of color image sharpening using nonlinear operations in HSV color space. Two different types of color image sharpeners have been designed, by taking advantage of operations used in mathematical morphology. The first sharpener utilizes fully-color pseudo top-hats transformations. The second one is a three-state toggle contrast operator and it uses two well-known morphological primitives i.e. erosion and dilation.*

Streszczenie. *W artykule tym przedstawiono koncepcję wyostrzania obrazów kolorowych za pomocą operacji nieliniowych wykonywanych w przestrzeni kolorów HSV. Zaprezentowano dwa rodzaje opracowanych operatorów kontrastowych wykorzystujących operacje morfologii matematycznej. Pierwszy operator poprawiający ostrośc obrazu wykorzystuje operację w pełni kolorowego przekształcenia quasi-cylindrycznego. Drugi operator wyostrzania jest trójstanowym operatorem kontrastowym przełączalnym i wykorzystuje on podstawowe operacje morfologiczne tj. erozję i dylację.* ***(Nieliniowe wyostrzanie obrazów w przestrzeni HSV)***

Keywords: cololor image sharpening, HSV color space
Słowa kluczowe: wyostrzanie obrazów kolorowych, przestrzeń kolorów HSV

Introduction

There is a lot of pictures suffering from low contrast pheomenon. In mamy cases this fact reduces the visual quality of an image which is shown to the human viewer. Sometimes the image quality is completely unaccaptable, in particular in pattern recognition applications. There are many examples of such defocoused pictures, specially in the area of old pictures which are important for the cultural heritage of human beings like artistic wall-paintings (e.g. old church paintings), frames taken from old motion pictures etc. In order to significantly improve the overall quality of such pictures, contrast sharpening or contrast enhancement processed should be used to increase the unsatisfying contrast of the original images.

HSV color space

The visual sensations caused by color light are significantly richer than those caused by achromatic light. Considering color perception phenomenon we usually use three main quantities known as hue, saturation and value (lightness, brightness). The *hue* component distinguishes among colors and controls the color spectrum from red through green, blue to violet. It is an attribute asociated with the dominant wavelength in a mixture of light waves and it represents dominant color as perceived by an observer. The *saturation* component controls the purity of the color, or how wash out the color is with white light (so it refers to relative purity or the amount of white light mixed with a hue). This parameter tells us how far color is from a grey of equal intensity. For instance a hue of red can have many different levels ranging from pure deep red (fully saturated) to pink (relatively saturated) and finally white (zero saturation at all). The third parameter is the *value* component (brightness, lightness) and it controls how bright the color appears (so it refers to the perceived intensity of an object). The value (brightness) parameter is a subjective descriptor, that is very difficult to measure. It embodies the achromatic notion of intensity and therefore it is one of the most important factors in describing color sensation.

Ordering taxonomy

There are many concepts of ordering the multivariate data in image processing literature. Even in the HSV representation only more than a dozen of ordering methods exists. For example, it is a relatively easy task to present at least two different versions of the lexicographic ordering approach [11]. There is no obvious (direct) ordering for color pixels due to lacking of natural ordering scheme in the vector field (for multivariate data). In order to deal with this severe problem many different algorithms have been proposed and they can be divided in four main groups [4]: mariginal ordering (M–ordering), conditional ordering (C–ordering), partial ordering (P–ordering), reduced (aggregate) ordering (R–ordering).

In marginal ordering, the color vectors are ordered in each component independently (another name for this approach is componentwise or poinwise ordering). This method has some advantages like for example implementational simplicity and high compatibility with scalar image processing algorithms. It suffers however, from two disadvantages: neglecting of inter–channel information and the danger of changing the spectral composition of its input. In addition to that, there is no guarantee that marginally ordered pixels belong to the input image. On the contrary it happens quite often that the method generates a set of ordered vectors that is different from the set of input pixels. For instance in the case of color image processing this may lead to the apperance of new colors. Another unwanted phenomenon here is a visually irritating effect in image called edge–jitter.

In conditional ordering (C–ordering) color pixels are ordered based on the marginal ordering of one or more of the components. The application of C–ordering to the color images preserves the input vectors (no colors, no edge jitter) The drawback of the C–ordering is high computational cost of the algorithms leading to inefficient, slow implementations. Obvieously the main problem here is the proper choice of the ordered components.

In reduced (aggregate) ordering each multivariate sample is reduced to a scalar value which is a function of the component values for that observation, with the multivariate samples ranked according to this single value (im accordance with this measurement). In order to present this kind of sorting strategy let $\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_n$ be a set of multivariate observations where each sample $\mathbf{p}_i$ is a vector in k–dimensional vector space (i.e. in $\mathbf{R}^k$). The n–samples should be sorted in accordance with a reduced ordering method. The first stage of this approach is to map each vector $\mathbf{p}_i$ to a scalar value $f_i = f(\mathbf{p}_i)$ where $f : \mathbf{R}^k \mapsto \mathbf{R}$ [6].

This way each color pixel $\mathbf{p}_i$ is represented by a scalar value and the $\mathbf{p}_1, \mathbf{p}_2, \ldots, \mathbf{p}_n$ are ordered according to these scalar values $f_1, f_2, \ldots, f_n$ in the following way: $\mathbf{p}_{(1)} \leq \mathbf{p}_{(2)} \ldots, \mathbf{p}_{(n)}$ Here $\mathbf{p}_{(r)}$ denotes the vector with corresponding scalar value $f_{(r)}$, where $f_{(r)}$, is the r–th smallest element of the collection $\{f_1, f_2, \dots, f_n\}$.

A commonly applied metric is the generalize distance to so–called a reference point $\mathbf{p}_{ref}$ using a covariance matrix $\mathbf{\Gamma}$ that represent the reliability or scale of the measurement in each direction:

$$d_i = (\mathbf{p}_i - \mathbf{p}_{ref})\mathbf{\Gamma}^{-1}(\mathbf{p}_i - \mathbf{p}_{ref}) \tag{1}$$

A problem exists in R-ordering when two distinct pixels give the same metric value.

The main problem with reduced ordering method is the uniqueness of the f mapping. It may be demonstrated that if we want to eliminate false colors phenomenon in the image it is sufficient to find an injective function, that maps the multivariate pixels to a complete lattice [7].

One of the most often encountered filter acting on color images and utilizing the R-ordering scheme is the Vector Median Filter [1]. In this filter the aggregate distance to all observation vectors is calculated for each observation (for color pixel).

Top-Hat Based Contrast Operator for Image Sharpening

The bright full color pseudo-tophat (BFCTH) can be defined as:

$$BFCTH_X^{+}(\mathbf{f}) = \mathbf{f} - \gamma_X(\mathbf{f}) \tag{2}$$

Similarily, the dark full color tophat (DFCTH) can be written as:

$$DFCTH_X^{-}(\mathbf{f}) = \phi_X(\mathbf{f}) - \mathbf{f} \tag{3}$$

By the analogy to the grey-level case the contrast operator based on these pseudo top-hats operations is obtained.

$$CONTH_X(\mathbf{f}) = \mathbf{f} + BFCTH_X^{+}(\mathbf{f}) - DFCTH_X^{-}(\mathbf{f}) \tag{4}$$

Therefore finally we get the more simple form of this equation:

$$CONTH_X(\mathbf{f}) = 3 * \mathbf{f} - \gamma_X(\mathbf{f}) - \phi_X(\mathbf{f}) \tag{5}$$

Contrast Sharpening with Ordering based on Physical Meaning of Mixing Colors with Black and White

One of the most interesting ordering algorithm is the method based on the physical meaning of mixing colors with white and black and on taking into account the amount of the two last factors [17]. This type of ordering has quite simple physical interpretation: the darker a color the smaller it is considered regardless the hue. The most important component in the HSV color space is the value (luminance) V.

So in the HSV representation first vectors (i.e color pixels) are sorted with respect to the third component – value V. All pixels are sorted from these with smallest Value (V) to those with greatest Value (V). So the HSV hexcone is divided into slices (levels), which are vertical to its height. Each lower level having a given value V is less then all higher slices (levels) corresponding to greater values of the third component V. Pixels with same V – value are next sorted with respect to the second components – S. The ordering is performed from the pixels with greatest S to the pixels with smallest S. So at a particular level any external hexagon with corresponding S–component is less than all hexagones that are included in it which correspond to smaller S – components. Therefore the most external hexagon with $S = 1$ is the smallest one, and the grey-level hexagon (reduced to a point) with S is the greatest. At last pixels which have the same saturations S are sorted starting from these with smallest hue to those with greatest hue.

Now we can define the following ordering relation as:
$\Lambda = \{||\cdot||_{\triangle}^{HSV}, V\uparrow \to S\downarrow \to H\uparrow\}$
where $\triangle$ is the color distance, $\uparrow$ means an increasing order (e.g. $V\uparrow$ means that V -values are ordered from the smallest one up to the greatest one), and $\downarrow$ denotes an decreasing order.

The ordering relation Λ based on physical meaning of mixing colors with black and white is a relatively new approach. Two color pixels $\mathbf{p}_i$ and $\mathbf{p}_i$ can be ordered acording the following rule [17]:

$$\mathbf{p}_i <_{\Lambda} \mathbf{p}_j \iff \begin{cases} p_i^V < p_j^V \; or \\ p_i^V = p_j^V \;\&\; p_i^S > p_j^S \; or \\ p_i^V = p_j^V \;\&\; p_i^S = p_j^S \;\&\; d(p_i^H, H_{ref}) < d(x_p^H, H_{ref}) \end{cases} \tag{6}$$

where pixel hue distance to the reference hue can be expressed as:

$$d(p_i^H, H_{ref}) = \begin{cases} |p_i^H - H_{ref}| \;\; if \;\; |p_i^H - H_{ref}| \le \pi \\ 2\pi - |p_i^H - H_{ref}| \;\; if \;\; |p_i^H - H_{ref}| > \pi \end{cases} \tag{7}$$

Contrast Sharpening with Classical Lexicographical Ordering

Lexicographical ordering is especially suitable for arranging pixels (vectors) in the context of color Mathematical Morphology, in combination with image data where a natural or artificial priority order exists among the different bands. As concerns the HSV model the hierarchy of importance proposed in [11] was used. It looks very natural for a human viewer system. In the HSV space the V coordinate is the most important one, the S coordinate is less important one, and H is the least important one. We define the following ordering relation as:
$\Omega = \{||\cdot||_{\triangle}^{HSV}, V\uparrow \to S\uparrow \to H\uparrow\}$
where $\uparrow$ means increasing order (e.g. $V\uparrow$ means that V - values are ordered from the smallest one up to the greatest one). The relation Ω is actually the Classical Lexicographical Ordering.

Two color pixels $\mathbf{p}_i$ and $\mathbf{p}_i$ can be ordered acording the following rule:

$$\mathbf{p}_i <_{\Omega} \mathbf{p}_j \iff \begin{cases} p_i^V < p_j^V \; or \\ p_i^V = p_j^V \;\&\; p_i^S < p_j^S \; or \\ p_i^V = p_j^V \;\&\; p_i^S = p_j^S \;\&\; d(p_i^H, H_{ref}) < d(p_j^H, H_{ref}) \end{cases} \tag{8}$$

where the pixel hue distance to the reference hue $d(p_i^H, H_{ref})$ is given by equation (7).

Contrast Sharpening based on Ordering associated with a reference color and completed with a lexicographical cascade

Another interesting pixel arranging scheme is total ordering asociated with a reference color. The authors of [13] proposed color morphological operators for which they define a reference being analogous to the maximum greylevel in greyscale morphology. Color dilation should tend toward this chosen refence color. On the contrary color erosion should tend away from it. In [13] it was shown that the reference color must have maximum luminance and maximum saturation to enable ordering of color pixels. The generalization of this approach was presented in [2].

The idea of distance to reference based on grey-level image morphology can be extended to multivariate data. We apply this approach to color pixels in the HSV space. We chose the reference color $\mathbf{p}_0$ and the color distance $\triangle$ and define the following ordering relation for two color pixels $\mathbf{p}_i, \mathbf{p}_j$:

(9) $$\mathbf{p}_i \prec \mathbf{p}_j \Leftrightarrow ||\mathbf{p}_i - \mathbf{p}_0||_{\triangle}^{HSV} > ||\mathbf{p}_j - \mathbf{p}_0||_{\triangle}^{HSV}$$

This system is only a partial ordering. For obtaining the total order Angulo in [2] propose to complete this primary reduced ordering with a lexicographical cascade. If we define this ordering scheme associated with a reference color and completed with a lexicographical cascade as:
$\Gamma = \{|| \cdot ||_{\triangle}^{HSV}, \mathbf{p}_0 = (p_0^H, p_0^S, p_0^V); V \uparrow \rightarrow S \uparrow \rightarrow H \uparrow\}$, where $\uparrow$ means increasing order (e.g. $V \uparrow$ means that V - values are ordered from the smallest one up to the greatest one), then two color pixels $\mathbf{p}_i$ and $\mathbf{p}_i$ can be ordered acording the following rule:

(10)
$$\mathbf{p}_i <_\Gamma \mathbf{p}_j \Leftrightarrow \begin{cases} ||\mathbf{p}_i - \mathbf{p}_0||_{\triangle}^{HSV} > ||\mathbf{p}_j - \mathbf{p}_0||_{\triangle}^{HSV} \ or \\ ||\mathbf{p}_i - \mathbf{p}_0||_{\triangle}^{HSV} = ||\mathbf{p}_j - \mathbf{p}_0||_{\triangle}^{HSV} \ and \\ \begin{cases} p_i^V < p_j^V \ or \\ p_i^V = p_j^V \ \& \ p_i^S < p_j^S \\ p_i^V = p_j^V \ \& \ p_i^S = p_j^S \ \& \ d(p_i^H, H_{ref}) < d(p_j^H, H_{ref}) \end{cases} \end{cases}$$

where $d(p_i^H, H_{ref})$ is given by equation (7).

Color Image Sharpening

Common image processing techniques for global contrast enhancement (e.g. global streching and histogram equilization) although often encountered do not always generate good results, specially for images with large spatial variation in the contrast. Some methods are also possible depending on image type for instance those using the retinex-theory [10],[5] , utilizing CLUM sharpener [14] , saturation or desaturation approach [12] or others [8].

Color Sharpeners based on Top-Hats

With this convention the bright full color pseudo-tophat (BFCPTH) for X–ordering (X = $\{\Lambda, \Omega, \Gamma\}$) is:

(11) $$BFCPTH_X^+(\mathbf{f}) = \mathbf{f} - \gamma_X(\mathbf{f})$$

Similarily the dark full color pseudo- tophat (DFCPTH) is:

(12) $$DFCPTH_X^-(\mathbf{f}) = \phi_X(\mathbf{f}) - \mathbf{f}$$

For color image with X–ordering we have:
(13)
$$CONPTH_X(\mathbf{f}) = \mathbf{f} + BFCPTH_X^+(\mathbf{f}) - DFCPTH_X^-(\mathbf{f})$$

Which is equal to:

(14) $$CONTPH_X(\mathbf{f}) = 3 * \mathbf{f} - \gamma_X(\mathbf{f}) - \phi_X(\mathbf{f})$$

Toggle Contrast Operator for Color Image Sharpening

Another posibility of using Mathematical Morphology for color image contrast enhancement is a concept of using toggle mappings. For grey-level images the contrast toggle mapping is defined by taking advantage of two factors. The first factor is choosing two primitives ϕ_1 and ϕ_2 which are applied to the initial image. The second factor is a decision rule which makes at each point $x = (x_1, x_2)$ the output of this mapping toggle among three possibilities ϕ_1, ϕ_2 and $f(x)$, depending on to which is the closest to the input value of the function f at x. Extending this approach to multichanel data (color image $\mathbf{f}$) with dilation (i.e. $\phi_1(\mathbf{f}) = \delta_X(\mathbf{f})$) and erosion (i.e. $\phi_2(\mathbf{f}) = \epsilon_X(\mathbf{f})$) as two primitives we propose the following three-state contrast operator with X–ordering (where X = $\{\Lambda, \Omega, \Gamma\}$) applied to the image $\mathbf{f}$ at point $x = (x_1, x_2)$ (pixel coordinates in image) as:
(15)
$$\kappa_X^{\epsilon,\delta}(\mathbf{f})(x) = \\ = \begin{cases} \delta_X(\mathbf{f})(x) \ if & ||\delta_X(\mathbf{f})(x) - \mathbf{f}(x)|| < ||\mathbf{f}(x) - \epsilon_X(\mathbf{f})(x)||/2 \\ \mathbf{f}(x) \quad if & \begin{cases} ||\mathbf{f}(x) - \epsilon_X(\mathbf{f})(x)||/2 \leq ||\delta_X(\mathbf{f})(x) - \mathbf{f}(x)|| \ \& \\ ||\delta_X(\mathbf{f})(x) - \mathbf{f}(x)|| < 2 * ||\mathbf{f}(x) - \epsilon_X(\mathbf{f})(x)|| \end{cases} \\ \epsilon_X(\mathbf{f})(x) \ if & \begin{cases} ||\delta_X(\mathbf{f})(x) - \mathbf{f}(x)|| \geq 2 * ||\mathbf{f}(x) - \epsilon_X(\mathbf{f})(x)|| \ \& \\ ||\delta_X(\mathbf{f})(x) - \epsilon_X(\mathbf{f})(x)|| \geq ||\delta_X(\mathbf{f})(x) - \mathbf{f}(x)|| \end{cases} \end{cases}$$

Contrast Measure for Color Image

There are different contrast measures in scientific papers but in this paper a very simple and practical definition is proposed which is based on the squared difference between the maximal and minimal elements withing the filtering mask. The mean contrast measure for the the image is:
(16)
$$MCM(i,j) = \frac{1}{KL} (\sum_{i=1}^{n} \sum_{j=1}^{m} \sum_{k=1}^{3} (y_{max}(i,j,k) - y_{min}(i,j,k))^2)$$

where the filtering mask (i.e. the morphological structuring element) has the size of $m \times n$ pixels and K, L are image dimensions.

Experiments

Experiments have been performed with two classes of color image of low contrast. The first one includes some sort of blur and it was taken from an old movie. The second type is the church painting with low contrast (slightly faded colors). Three types of ordering have been applied. The size of the filtering mask (the structuring morphological element) was 5×5 pixels. The color distance $\triangle$ for all the experiments was L_2 norm.

Results

The first operator, which is based on full color pseudo-tophats acts sometimes too strong. It works good for an image of church paintings but for images taken from old movies it sharpens too much and in addition to that it introduces color changes near the border of some objects (human figures). For the old film image the contrast sharpening achieved with the new three step toggle mapping is visually good. The key issue here is to choose two primitives properly. For example , this contrast operator performs significantly better for erosion and dilation pair then for opening and closing pair of primitives. The ordering type used for morphological operations has only a very small influence on final results. However in the case of image presenting the old church painting the three-state toggle based sharpener is partially acceptable only for Λ–ordering and Γ–ordering (mean contrast measure has increased from 0.33 to about 0.38). As concerns Ω–ordering here , the results were unaccaptable (mean contrast measure has even decreased slightly). On the other hand the contrast sharpener based on full color pseudo-tophats operators significantly outperforms the three-state color contrast sharpener when dealing with images of church paintings.

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Table 1. Contrast measure for sharpened image1 (orig.= 0.1191)

Ordering type	Pseudo Top-Hat	Three-State Toggle
Λ	0.1620	0.1331
Ω	0.1709	0.1301
Γ	0.1631	0.1329

Table 2. Contrast measure for sharpened image2 (orig. = 0.3333)

Ordering type	Pseudo Top-Hat	Three-State Toggle
Λ	0.7210	0.3791
Ω	0.7768	0.3312
Γ	0.7214	0.3781

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Fig. 1. The blurried image from an old movie

Fig. 2. Result of contrast sharpening by three-state operator operator (DE) with Λ ordering

Fig. 3. Result of contrast sharpening by three-state operator with Γ ordering

Fig. 4. Result of contrast sharpening by three-state operator with Ω ordering

Fig. 5. Result of contrast sharpening by TopHat operator with Λ ordering

Fig. 6. Result of contrast sharpening by TopHat operator with Γ ordering

Fig. 7. Original image of church paintings

Fig. 8. Sharpening of church paintings by morphological operator based on pseudo TopHat with Λ-ordering

Fig. 9. Sharpening of church paintings by three–state morphological operator with Λ-ordering