

Further Enhanced Image-Colour-Transfer

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A Further Enhanced Implementation of the Colour Transfer Method Proposed by E Reinhard et al.

Introduction

The author of this document has previously suggested an enhancement to the method of image colour transfer developed by Reinhard et al [Ref 1]. The enhanced method in common with the original requires manipulation of the mean and standard deviation values of the image as represented in the $l\alpha\beta$ colour space method, but in addition requires manipulation of the cross correlation between the ' α ' and ' β ' colour components [Ref 2]. The new implementation proposed here also requires the manipulation of the mean, standard deviation cross correlation values, but additionally offers further options for improved colour transfer that are different to those offered to date. These options address the reshaping of data within the ' α ' and ' β ' colour components and the adjustment of image colour saturation. Additional options are offered for the conditioning of image shading.

The Reinhard Colour Transfer Method

Reinhard et al presented a method for matching the colour distribution of a target image to that of a source image by use of a linear transform in the $l\alpha\beta$ perceptual colour space so as to match the mean values and standard deviations of the target image to those of the source image along each of the colour space axes. By resetting the parameters of the target image to match those of the source image, the colour information in the target image is modified to better resemble that of the source image.

The processing steps are as follows.

1. Convert the both the source and target images from RGB colour space to $l\alpha\beta$ colour space
2. Compute the mean and standard deviation of each of the three ' l ', ' α ' and ' β ' components for both images.
3. Standardise the three components of the target image by subtracting the respective mean values and dividing by the respective standard deviation values.
4. Reformulate new target values by applying the respective source standard deviations as scaling factors to the standardised components and adding in the source mean values.
5. Convert the resultant from $l\alpha\beta$ colour space to obtain the output image in RGB colour space.

The third and fourth steps can be represented as follows.

$$z_c = (x_c - \hat{\mu}_{tc}) / \hat{\sigma}_{tc} \quad X_c = z_c * \hat{\sigma}_{sc} + \hat{\mu}_{sc} \quad \text{for outputs } X_l, X_\alpha, X_\beta, \text{ and inputs } x_l, x_\alpha, x_\beta.$$

Effectively here, the x_l, x_α , and x_β values are reworked for every pixel in the target image so that collectively their mean values and their standard deviations are reset to match the values observed in the colour source.

Processing is performed in the $\alpha\beta$ colour space because the three components in this space have been observed to show low inter-dependency for certain classes of natural imagery and it can be more acceptable to process components independently in this colour space.

The Enhanced Colour Transfer Method

The basis of the enhanced colour transfer method is as follows.

Let s_1 and s_2 be two independent (zero correlation) variables with mean values equal to zero and standard deviations equal to one. It possible to construct variables a_1 and a_2 with mean values equal to zero and standard deviations equal to one but with mutual cross correlation 'R' by means of the following operations.

$$a_1 = \sqrt{\frac{1+R}{2}} \times s_1 + \sqrt{\frac{1-R}{2}} \times s_2 \quad \text{and} \quad a_2 = \sqrt{\frac{1+R}{2}} \times s_1 - \sqrt{\frac{1-R}{2}} \times s_2$$

Conversely, the inverse relations can be applied to derive independent variables s_1 and s_2 from correlated variables a_1 and a_2 .

$$s_1 = \frac{a_1 + a_2}{\sqrt{0.5 \times (1+R)}} \quad \text{and} \quad s_2 = \frac{a_1 - a_2}{\sqrt{0.5 \times (1-R)}}$$

The enhanced colour transform method incorporates additional steps compared to the original method by which the correlation between the colour components ' α ' and ' β ' is modified so that it corresponds to the value observed in the colour source image rather than that in the target image.

This can be achieved by inserting additional steps into the previously described method as follows.

- 3.0 Standardise the three components of the target image by subtracting the respective mean values and dividing by the respective standard deviation values.
- 3.1 Cross-multiply the corresponding values of the ' α ' and ' β ' components and hence determine the average cross product value for both the target and source images.
- 3.2 Denote the two average cross products as the correlation values \hat{R}_t and \hat{R}_s respectively.
- 3.3 Using the value \hat{R}_t , which represents the correlation between the ' α ' and ' β ' channels in the target image, form new independent variables from the values z_α and z_β .
- 3.4 Using the value \hat{R}_s , which represents the correlation between the ' α ' and ' β ' channels in the sample image, form new standardised variables z'_α and z'_β with correlation value \hat{R}_s .
- 4.0 Reformulate new target values by applying the respective source standard deviations as scaling factors to the (modified) standardised components and adding in the source mean values.

The new intermediate steps can be represented as follows.

The correlation values are computed as follows.

$$\hat{R}_t = \frac{1}{n} \sum Z_{t\alpha}(i) * Z_{t\beta}(i) \quad \text{and} \quad \hat{R}_s = \frac{1}{m} \sum Z_{s\alpha}(i) * Z_{s\beta}(i)$$

The standardised colour components are modified as follows.

$$s_{\alpha} = \frac{z_{t\alpha} + z_{t\beta}}{\sqrt{0.5 \times (1 + \hat{R}_t)}} \quad \text{and} \quad s_{\beta} = \frac{z_{t\alpha} - z_{t\beta}}{\sqrt{0.5 \times (1 - \hat{R}_t)}}$$

$$z'_{\alpha} = \sqrt{\frac{1 + \hat{R}_s}{2}} \times s_{\alpha} + \sqrt{\frac{1 - \hat{R}_s}{2}} \times s_{\beta} \quad \text{and} \quad z'_{\beta} = \sqrt{\frac{1 + \hat{R}_s}{2}} \times s_{\alpha} - \sqrt{\frac{1 - \hat{R}_s}{2}} \times s_{\beta}$$

In the former relationships the 'n' and 'm' values denote the number of pixels in the respective images. In the latter relationships, the transforms are applied to each pixel within the target image. Note that the computation of correlation values normally requires the subtraction of mean values and division by standard deviation values, but this is not necessary here because the correlation is computed directly from standardised values which have already been pre-processed.

The implementation described in this document uses the $\text{L}\alpha\beta$ colour space rather than the Cielab $\text{L}^*\text{a}^*\text{b}$ colour space. Reinhard and Pouli [Ref 3] found that $\text{L}^*\text{a}^*\text{b}$ mostly outperforms $\text{L}\alpha\beta$ for colour transform processing. However, their study was based upon the assumption that cross correlation should be addressed by choice of colour transform rather than explicit processing. Evidence reported elsewhere [Ref 2] suggests that in practice processing based upon the $\text{L}\alpha\beta$ colour space is more robust.

Alternative Formulation

The intermediate steps 3.1 to 3.4, as described previously, can be represented as follows.

$$z_{\alpha} = W_1 z_{t\alpha} + W_2 z_{t\beta} = \frac{1}{2} \left[\sqrt{\frac{1 + \hat{R}_s}{1 + \hat{R}_t}} + \sqrt{\frac{1 - \hat{R}_s}{1 - \hat{R}_t}} \right] z_{t\alpha} + \frac{1}{2} \left[\sqrt{\frac{1 + \hat{R}_s}{1 + \hat{R}_t}} - \sqrt{\frac{1 - \hat{R}_s}{1 - \hat{R}_t}} \right] z_{t\beta}$$

$$z_{\beta} = W_1 z_{t\beta} + W_2 z_{t\alpha} = \frac{1}{2} \left[\sqrt{\frac{1 + \hat{R}_s}{1 + \hat{R}_t}} + \sqrt{\frac{1 - \hat{R}_s}{1 - \hat{R}_t}} \right] z_{t\beta} + \frac{1}{2} \left[\sqrt{\frac{1 + \hat{R}_s}{1 + \hat{R}_t}} - \sqrt{\frac{1 - \hat{R}_s}{1 - \hat{R}_t}} \right] z_{t\alpha}$$

The output standardised variables are computed as weighted sums of the input standardised variables. Each output channel is derived as a scaled contribution from the corresponding primary input colour channel plus a contribution from the other secondary channel. If the contribution from the secondary channel is zero then the original Reinhard method is implemented with no additional enhancement processing. If the contribution from the secondary channel is similar in size to that from the first channel then the colour transfer can sometimes be too intense and the colouring can appear somewhat artificial. To address this, the enhanced implementation of colour transfer incorporates an option to limit the size of the secondary channel contribution relative to that of the primary channel. Even when limiting is applied some level of additional colour enhancement will be implemented over and above that of the standard processing method.

Colour Channel Data Reshaping

A new option is proposed here to facilitate improved matching of the colour channels (the ' α ', ' β ' channels) by addressing moments beyond the second order moments of the data. The original Reinhard method resets the mean and standard deviation values of each the target image colour channels to match those of the source image. This ensures that each target channel has the same

average location and average dispersion as the corresponding source channel but it does not ensure that other characteristics are matched. If for example, a source channel has a concentration of data values at the upper end of the permitted range and the target channel has a concentration of data values at the lower end of the permitted range, then this difference would persist after processing. Indeed a further issue could arise because, by matching the mean and standard deviation values of disparate distributions it could be that some of the target values might be shifted outside of the permitted range and they would need to be clipped within range before display. A further issue could arise when cross correlation processing is applied since this can further alter the data distribution within a target channel.

The new shaping algorithm attempts to match higher moments of the colour channel distributions in addition to the first second order moments. At first sight, it might be thought that any colour transfer processing method should aim to match the colours in the target image to those in the source image as closely as possible. In practice this can be problematic. Pitie et al [4] explain this as follows. *“Consider a pair of landscape pictures where the sky in one picture covers a larger area than in the other. When transferring from one picture to the other, the excess of sky colour may be used in parts of the scenery on the ground in the other.”* Furthermore, Faridul et al [5] report that for close correspondence colour mapping *“the resulting image may be too harsh as the transfer can amplify artefacts that were previously invisible, indicating that higher-order properties of the image may need to be matched or preserved to achieve a successful result”*. The additional matching operations proposed here do not seem to exhibit these adverse effects despite their greater fidelity; perhaps because that fidelity is achieved in the $\alpha\beta$ colour space and then only for the ‘ α ’ and ‘ β ’ components.

A feature of the standard Reinhard processing is that processing is performed in the $\alpha\beta$ colour space. This space is a logarithmic space and conversion back to BGR space requires exponentiation. If the target image is not well matched to the source image in $\alpha\beta$ colour space, then the process of exponentiation can greatly amplify any discrepancy. This is one reason to consider additional processing for greater fidelity.

It can be noted that the basic Reinhard processing method considers the average deviation of channel data from the mean within the source image and rescales the deviations in the target image to achieve the same average deviation (measured in terms of root mean square). If the channel data is skewed, then the average deviation above the mean will be different from the average deviation below the mean. It follows that greater fidelity can be achieved by separately processing data values above and below the mean. If the data has a severe skew then in practice the mean value might not be the ideal reference point, nevertheless it will generally be more effective to apply separate processing to data above and below the mean than to apply common processing to both data sets as in the basic Reinhard method.

A second feature of the basic Reinhard method is that rescaling is applied uniformly to target deviations irrespective of the distance from the mean. If the data in a target image channel is concentrated at the centre of the permitted range but in the source image at the extremes of the permitted range then this difference will not be addressed in standard Reinhard processing. Such a difference is a characteristic of the kurtosis or fourth order moments of the data, so processing based upon second order moments will have little effect. Greater fidelity can only be achieved by

allowing for the possibility that different scaling will need to be applied to channel values exhibiting small deviations from the mean than to those exhibiting large deviations from the mean.

The shaping processing to match a target image colour channel to a source image target channel is as follows.

For a colour channel of the target image, for those values that lie above mean, compute a weighted average of the 4th moment as follows. This is a weighted estimate of (upper) kurtosis.

$$W_{mean_target_upper} = \frac{\sum W_i [z(u)_i]^4}{\sum W_i} \quad \text{here} \quad z_i = (x_i - \hat{\mu}_c) / \hat{\sigma}_c \quad \text{and}$$

$$W_i = W(z_i) \text{ if } z_i > 0$$

$$= 0 \text{ otherwise.}$$

Here $\hat{\mu}_c$ and $\hat{\sigma}_c$ are the computed values of the mean and standard deviation respectively of all the data values within the target colour channel. The weighting value $W(z_i)$ is dependent upon the value of z_i as will be described later.

A similar computation can be performed for the corresponding source target channel and a scaling value $k_{scaling_upper}$ can be computed as follows.

$$k_{scaling_upper} = \sqrt[4]{\frac{W_{mean_source_upper}}{W_{mean_target_upper}}}$$

The quantity $k_{scaling_upper}$ is the fourth root of the ratio of two weighted estimates of kurtosis for the positive values within the source image channel and the target channel respectively. For convenience it will be denoted as ‘the weighted kurtosis ratio’. Once the value of $k_{scaling_upper}$ has been determined the data values within the colour channel of the target image that are greater than the mean are scaled as follows.

$$z'_i = (1 + W_i(k_{scaling_upper} - 1)) * z_i$$

The weighting function W_i is chosen so that it is zero for values of z_i equal to (or less than) the mean, near zero for values close to the mean and approaching unity for values that are significantly above the mean. The operation specified above therefore leaves values below and equal to the mean unchanged but values that are significantly above the mean are approximately scaled by the factor $k_{scaling_upper}$ which is the weighted kurtosis ratio of the source relative to image the target. If the source image channel has a long positive tail compared to the target channel then the kurtosis ratio will be greater than unity and the tail of the target image values will be extended outwards. If the source image channel has a short positive tail compared to the target channel then the kurtosis ratio will be less than unity and the tail of the target image values will be pulled inwards.

Similar processing can be applied to the negative channel values. (Conceptually, one could negate the channel data, apply the same processing procedure as before and then negate the outcome.)

The processing as describe will produce target colour channel data whose mean is no longer exactly equal to zero and whose standard deviation is no longer equal to unity. To address this, the data is subsequently re-standardised to achieve exact normalisation.

It can be seen that the process described above can adjust the negative and positive tails of the data in the colour channel of the target image to more closely resemble the negative and positive tails in the same colour channel of the source image. Thus the target image data is shaped to match the skewness and kurtosis observed in the source image data. This matching is achieved by utilising any weighting function which, for a given set of observations, has zero weighting for small observations and unity weighting for very large observations. The actual weighting function used has been determined by trial and error and can be inspected in the implementation code.

In practice, if the process described here is applied once to the ' α ' and ' β ' channels, then an improved match may be achieved but not necessarily a good match. To achieve a good match, it may be necessary to process more than once iteratively. If a single iteration is applied it should be implemented to the standardised data immediately after correlation matching. If two or more iterations are applied, then shape matching processing should be applied both before and after correlation matching.

The following shows an example where the original Reinhard processing is implemented followed by cross correlation processing and where subsequently zero and four iterations of reshaping are preformed.



Source and Target Image

No Shaping Processing

Subsequent to 4 Shaping Iterations

The following table shows, for the image above, the progression of the image characteristics over successive iterations.

Target Image	α Channel		β Channel	
Iterations	Skewness	Kurtosis	Skewness	Kurtosis
0	4.270	33.417	2.007	9.398
1	1.273	5.698	1.276	5.593
2	0.818	4.178	0.945	4.716
3	0.595	3.617	0.767	4.358
4	0.463	3.305	0.666	4.131
Source Image	-0.103	2.447	0.0968	3.3836

It can be seen that successive iterations modify the target image characteristics to more closely resemble the source image characteristics but the most predominant change is on the first iteration.

It can be seen that visually the target image after 4 iterations looks somewhat different than it does before the iterative processing, particularly in the lower left hand corner of the image, but the difference is not as dramatic as might be expected from the large change in the tabulated values. Here the colour source image has been chosen to be particularly vibrant and varied, whereas the target image is dull and uniform. For other image pairs with more similar properties the visual effect of channel shaping processing is even less noticeable. The author had found it difficult to identify an image pair which demonstrates a strong clear advantage for channel shaping. Practical experience across a variety of image combinations suggests that in most cases a single iteration is appropriate if any.

Saturation Processing

It has been observed that the process of modifying the target colour characteristics to match the source image characteristics can often lead to vibrant, perhaps even over vibrant colours. This can occur in particular when pure colour processing is applied; (a processing option that will be described later). Saturation processing is offered as an option to mute the colour intensity.

The idea of saturation processing is to adjust the saturation characteristics of the processed image to match the saturation characteristics of an artificially constructed image whose saturation characteristics are considered desirable.

The first stage of saturation processing is to convert the processed target image and the original target image into a HSV colour space representations and to extract the 'S' saturation channel from each. The next stage is to define a reference saturation channel S_{ref} as a weighted average of the two saturation channels as follows.

$$S_{ref} = \frac{percent_{sat}}{100} * S_{processed} + \left(1 - \frac{percent_{sat}}{100}\right) * S_{original}$$

Processing is then performed to form a modified reference channel as follows.

$$\begin{aligned} S_{refmod} &= S_{ref} & S_{ref} &> S_{original} \\ &= S_{original} & S_{original} &\geq S_{ref} \end{aligned}$$

The mean and standard deviation of the modified reference channel S_{refmod} is then computed and $S_{processed}$ is adjusted to match that mean value and that standard deviation.

An image in the BGR colour domain is then computed from its representation in the HSV domain using $H_{processed}$, $S_{adjusted}$ and $V_{processed}$. The resultant gives the new processed image with modified saturation with one exception. If $percent_{sat}$ is 100%, then the new image is set equal to the existing processed image unmodified.

If $percent_{sat}$ is specified to have a negative value then it is reset to the ratio of the largest value of $S_{modified}$ to the largest value of $S_{processed}$.

The preceding processing sequence gives an image with saturation similar to the original target image when $\text{percent}_{\text{sat}}$ is near to 0%, and similar to the processed image when $\text{percent}_{\text{sat}}$ near to 100%. It gives an intermediate saturation otherwise. For a negative value of $\text{percent}_{\text{sat}}$, the saturation is adjusted in accordance a computed value of $\text{percent}_{\text{sat}}$ as described previously such the largest saturation value in the modified reference saturation channel is equal to the largest saturation value in original target image.

For saturation processing, the saturation is computed as defined for the HSV colour space rather than the HSL colour space since the former appears to give a better outcome.

Examples of saturation processing are shown below, the '100% saturation' image corresponds to the '4 iterations' images shown above. The option for the automatic selection of saturation level would in this case give an outcome very close to 50% saturation.



Shading

Although the Reinhard method is called a colour transfer method, shading (lightness and darkness) is also transferred from the source to the target image. This is appropriate for an application such as image stitching because it is desirable that the constituent images be comparable in both colour and shading to ensure an invisible join. It is also appropriate in a situation, say, where colour transfer is applied to modify a daytime image to a night time scene. Strictly, however, the phrase 'colour transfer' implies the transfer of colour only and there are situations where this is desirable.

In the context of the Reinhard colour transfer method, the transfer of colour but not shading is a simple matter. In the standard approach, the lightness component of the target image is modified to match the lightness component of the source image using similar processing to that applied to the two colour components. In 'pure colour' processing the colour components are processed but the lightness component is left unmodified.

The processing here provides an option which allows the shading of the image to be varied.

The Reinhard processing of the lightness channel in the $\alpha\beta$ colour domain is modified to give a more general outcome. The processing is as follows.

$$z_l = (x_{l_target} - \hat{\mu}_{l_target}) / \hat{\sigma}_{l_target}$$

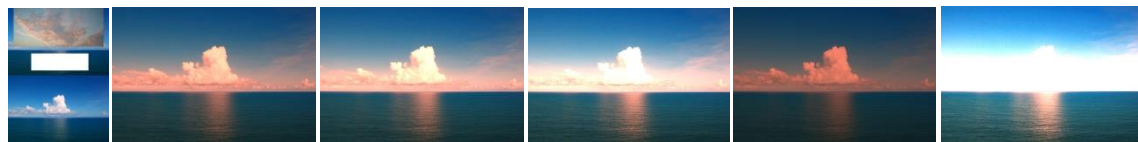
$$\hat{\mu}_{l_modified} = \frac{\text{percent}_{\text{shading}}}{100} * \hat{\mu}_{l_source} + \left(1 - \frac{\text{percent}_{\text{shading}}}{100}\right) * \hat{\mu}_{l_target}$$

$$\hat{\sigma}_{l_modified} = \frac{\text{percent}_{\text{shading}}}{100} * \hat{\sigma}_{l_source} + \left(1 - \frac{\text{percent}_{\text{shading}}}{100}\right) * \hat{\sigma}_{l_target}$$

$$X_l = z_l * \hat{\sigma}_{l_modified} + \hat{\mu}_{l_modified}$$

If percent_{shading} is set to 100%, then the original lightness channel in the target image is modified so that the channel mean and standard deviation are reset to equal the values of the source image lightness channel. This is standard Reinhard processing. If percent_{shading} is set to 0%, then the lightness channel is unchanged and the final image retains the shading properties of the target image. This is pure colour processing. Intermediate values of percent_{shading} give intermediate results. Values below 0% and above 100% are also permitted, although the ascetics of the outcomes may or may not be pleasing.

Examples of shading processing are given below. Here, in addition to shading, each image has been subject to cross correlation processing, 4 iterations of shaping and automatic saturation processing.



Source & target Shading percent =0 Shading percent =50 Shading percent =100 Shading percent =-100 Shading percent =200

Additional Shading Considerations

In addition to standard shading processing, a further additional shading processing option is offered. This option corrects the final image shading in the image domain to ensure that the grey shade representation of the final image has the same characteristics as the grey shade representation of the image defined by percent_{shading}. This can produce a different result from the simple shading procedure, as previously described, because the grey shade is typically defined as a linear combination of the blue, green and red content of the image but colour transfer can change the balance of those colours.

Additional shading adjustment allows for the fact that the eye has a different luminance response to different colours. A given level of green looks brighter than a given level of red which looks brighter than a given level of blue. If the colours within a pixel are changed then the perceived brightness may change even if the average level is unchanged. In the $\alpha\beta$ colour space the so-called luminance channel could be unchanged but the perceived brightness could be modified because of a redistribution of energy between the two the chromatic channels. So, for example, a change in the chromatic channel values which caused a shift from blue to green would cause an increase in perceptual brightness. The processing for the shading adjustment attempts to compensate for any perceived change in luminance due to colour modification.

The processing is as follows (for the case of percent_{shading} set to 100%).

In OpenCV a grey shade value is computed as follows.

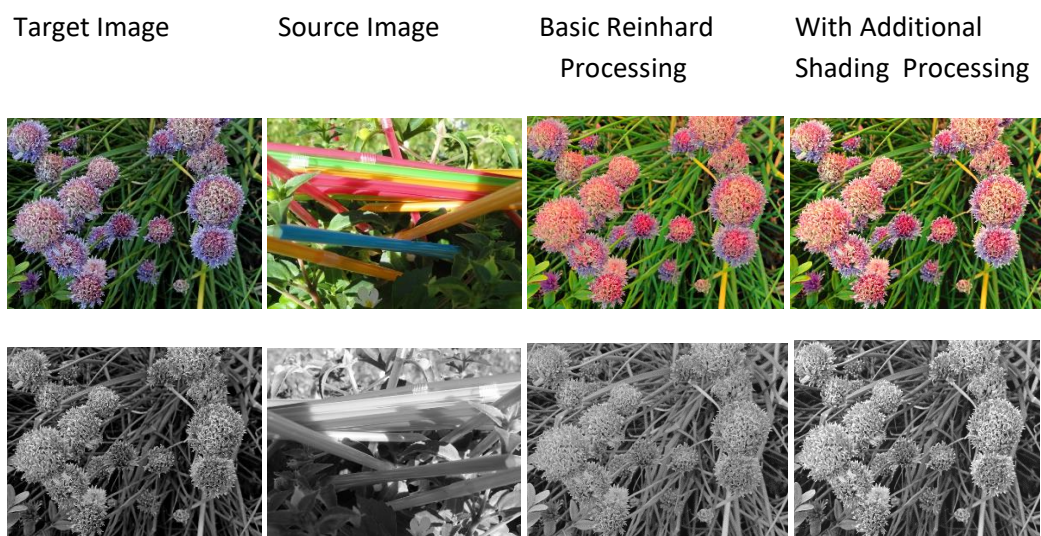
$$G = 0.299 * R + 0.587 * G + 0.114 * B$$

Let the mean and standard deviation of the grey-shade target image be denoted as $\hat{\sigma}_{Gt}$ and $\hat{\mu}_{Gt}$ and let the mean and standard deviation of the grey-shade source image be denoted as $\hat{\sigma}_{Gs}$ and $\hat{\mu}_{Gs}$ respectively. Furthermore, let the grey-shade value of a particular pixel within the grey-shade processed image be denoted as $G_0(i)$ and let the corresponding values within the target image be $G_t(i)$, then the RGB values for the particular pixel within the processed image are each multiplied by a factor 'R(i)'

$$\text{where } R(i) = \frac{1}{G_0(i)} \{ [(G_t(i) - \hat{\mu}_{Gt}) / \hat{\sigma}_{Gt}] * \hat{\sigma}_{Gs} + \hat{\mu}_{Gs} \}$$

In effect here, a given processed pixel is divided by its individual grey-scale value and then rescaled to achieve a greyscale value consistent with global adjustment of the greyscale values independent of any actual colour change. Individual brightness changes in individual processed pixels due to colour reformulation are therefore removed and a global change in greyscale is applied to match the global brightness characteristics of the source image (or a percentage of the source brightness if percent shading is not set to 100%.) It can be noted that because the factor R is applied to each of the colour channels, then the chromatic balance of the image is not affected only its brightness.

The correct processing of an image in terms of its brightness is important because it is the luminosity variation of an image which largely determines its perceived fidelity [Ref 6]. The human eye has around 100 million rod cells which are sensitive to luminosity but only 6 million rods which are sensitive to colour. The images below illustrate the importance of shading correction.



continued over

The following shows some of the previous images both before and after the application of further shading processing.

Before further shading:



After further shading



Shading percent =0

Shading percent =50

Shading percent =100

It can be seen that further shading produces a noticeable effect which is generally beneficial.

Further Options

Further options are provide to adjust the tint and the modification level of the image.

If percentage tint is set to 0%, the output image is monochrome. If it is set to 100%, the image is the fully coloured target image as conditioned by the processing that has been described here. Intermediate values give intermediate outcomes. Values below 0% and above 100% are also permitted, although the ascetics of the outcomes may or may not be pleasing.

If percentage modified is set to 0%, the output image is identical to the original target image. If it is set to 100%, the image is the modified image as conditioned by the processing that has been described here. Intermediate values give intermediate outcomes. Values below 0% and above 100% are also permitted, although the ascetics of the outcomes may or may not be pleasing.

continued over

Default Processing Values

The following processing parameter values are recommended as default.

- CrossCovarianceLimit : 0.5
- ReshapingIterations: 1
- PercentSaturationShift: -1.0
- PercentShadingShift: 50.0
- ExtraShading: true
- PercentTint: 100.0
- PercentModified: 100.0

PercentSaturationShift is set to negative which invokes automatic parameter determination. A single reshaping iteration is suggested. This is a compromise. Even a single iteration represents a substantial processing load which in many cases produces no noticeable effect, but in some extreme cases up to 4 iterations can achieve better fidelity. Below is an example, where shaping processing has a benefit. The parameters are set as above but the shaping iteration value is varied.



Source and
target
Images



No
shaping
iterations



One
shaping
iteration



Four
shaping
iterations

In this example, the three red 'blobs' on the second row blue brick show increasing fidelity with increasing iteration, but the majority of the benefit is achieved from just one iteration.

Observations

The enhanced colour transfer method achieves a potential advantage over the standard method by taking account of the correlation between the colour components in the $l\alpha\beta$ colour space. In some

image pairs it could be that the correlation is similar in both the target and the source image (perhaps even near to zero in both). Under such circumstances, enhanced processing will provide no benefit over standard processing although it should not give rise to any noticeable disadvantage.

A novel application for colour transfer is that of indirect colour shading. Here the colour source image is a modified version of the target image. As an example, consider a situation where it is required to adjust the sky colour in an image. Commercial software applications offer various tools to address this requirement, but an alternative and sometimes simpler approach would be to use indirect colour shading. Here, a duplicate of the original image would be taken and a block within the sky would be set to a different colour perhaps directly or perhaps by pasting from another image. The colour of the original target image would then be modified by the colour transfer from the customised source image. In the examples shown previously, the 'ocean scene' is an example of indirect colour shading.

The enhanced method of colour transfer only addresses the cross correlation between the colour components. It does not address any cross correlation between either of the colour channels and the lightness/darkness channel. It is not clear whether it would be useful to modify the target image to incorporate any relationship between colour and brightness as observed in the source image, let alone any dependency of brightness on colour. A brief and approximate investigation has been undertaken and this suggests that, in some circumstances, the transfer of colour brightness dependencies could create anomalous effects in the final image.

Published reviews of colour transfer methods often distinguish between photorealism and painterly effects. The latter addresses the process of generating images that mimic the colour palette and style of a particular artist such as Van Gogh or Seurat. The style of some artists is more susceptible to this process than others. Magritte and Dali, for example, are two artists whose style would be difficult to replicate by colour transfer methods since surrealist art depends more on image content than image rendition. Colour transfer does however, offer the interesting possibility of photo-surrealism, where colour transfer can be used to generate aesthetically pleasing images that look realistic but whose colours are clearly unreal. Such images typically look realistic in monochrome but not in colour.

Commercial photo processing applications offer options such as 'Solarize', 'Gradient Map' and 'Posterize' which can be used to transform images to achieve multi-colour or psychedelic outcomes. Colour transfer can also offer the possibility of colourful imagery but with the possibility of greater subtlety and control. The 'brick wall' imagery, that will be presented later, illustrates this.

Conclusion

The processing methods presented here extend the well known basic method of colour image transfer method developed by Reinhard et al. Arguably, these new methods have taken the mechanical algorithmic approach to whole image processing as far as possible for realistic natural colour transfer. The methods here show what can be achieved when processing load is not a consideration. For practical applications a trade off between image accuracy and processing load may be desirable.

Other algorithmic methods such as the author's own, proprietary, 'Adaptive Recolouring' method can offer better aesthetics for surrealistic re-colouring for artistic purposes. (See example which follows.)

Algorithmic methods may be extended by applying colour transfer methods to image segments or swaths taking account of image structure and content. Ultimately this leads to automatic methods using deep neural network. Such an approach can produce interesting results though it is sometimes difficult to judge the extent to which a network has been specifically tuned to particular image classes. At present, the neural methods are considered distinct from algorithm processing methods, but this need not necessarily be the case. It may be that there could be potential benefits from applying neural network methods to images that have been pre-processed by algorithmic methods. If an algorithmic method is assigned to do the 'heavy lifting' first then there could be greater potential for a neural method to provide a fine rebalancing of the image as a second stage. Alternatively, algorithmic methods might be used to post process images produced by neural networks just as saturation and additional shading are applied here to images that have already been conditioned by Enhanced Reinhard processing in $\alpha\beta$ colour space.

References

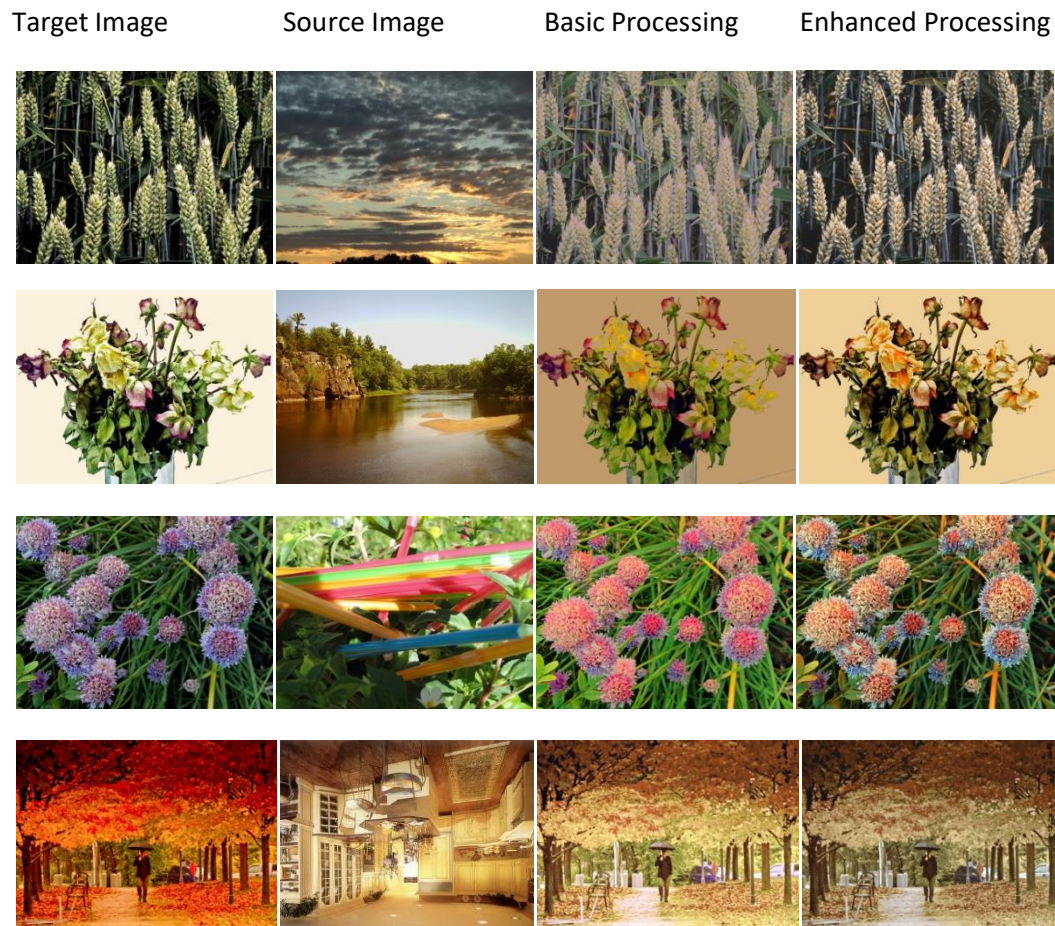
- [1] <https://www.cs.tau.ac.il/~turkel/imagepapers/ColorTransfer.pdf>
- [2] <https://github.com/TJCoding/Enhanced-Image-Colour-Transfer>
- [3] https://link.springer.com/content/pdf/10.1007%2F978-3-642-20404-3_1.pdf
- [4] <https://github.com/frcs/colour-transfer/blob/master/publications/pitie08bookchapter.pdf>
- [5] Faridul H S, Pouli T, Chamaret C, Stauder J, Tremeau A, Reinhard E. "A Survey of Color Mapping and its Applications. Conference: Eurographics 2014 - State of the Art Reports, 2014
- [6] Livingstone M," Vision and Art: The Biology of Seeing", Abrams, ISBN 978-1-4197-0692-9.

See overleaf for processing examples.

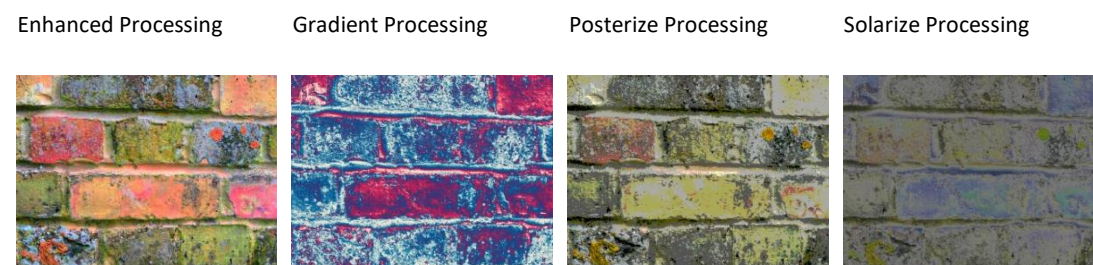
1. Processing Examples:

Various images are displayed below. There is a discussion of image quality thereafter.

In the examples below, 'Basic Processing' corresponds to simple Reinhard processing, whereas 'Enhanced Processing' corresponds to processing performed using the suggested default processing parameters.



2. Processing Comparisons:



Continued over

3. An Example of Photo-surrealism

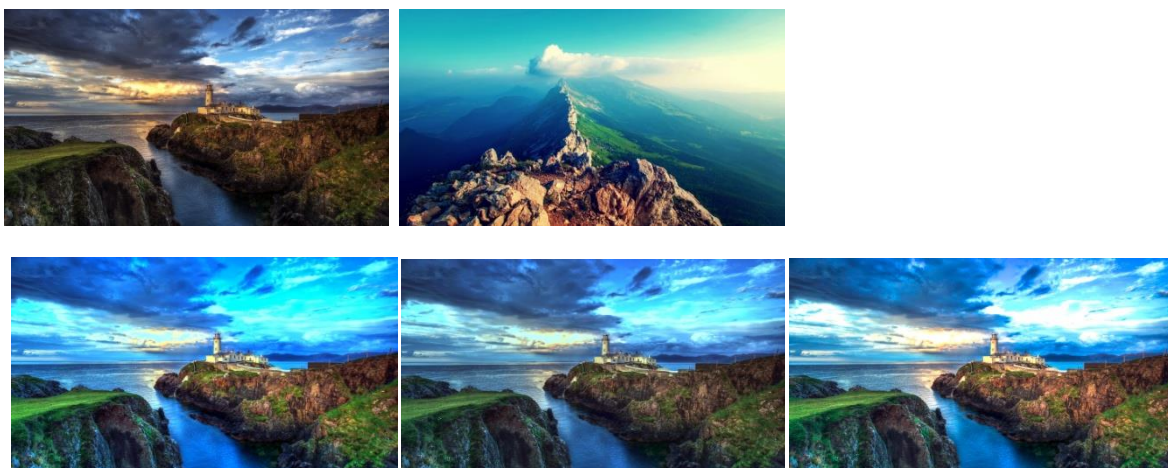
The image below was generated using 'Adaptive Re-colouring' a new processing method which is proprietary to T E Johnson. As with the preceding flower images, this image looks photorealistic in monochrome but the colouration is surreal. Further examples and discussion of this method can be found here <https://github.com/yciing/Neural-Style-Transfer-Papers/issues/14> .

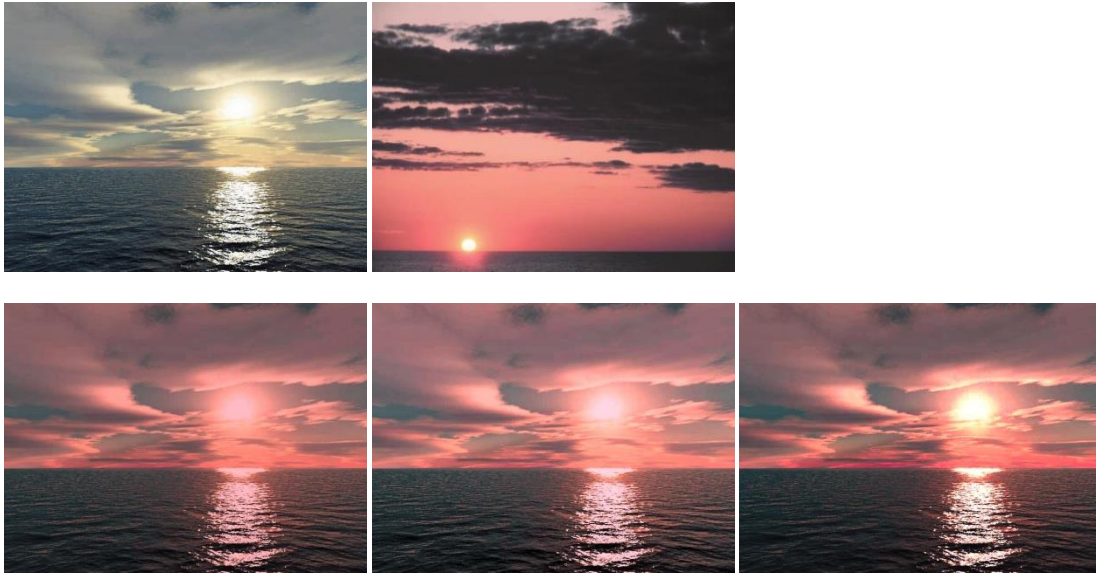


4. Further Comparisons

The following show processed images and allow a comparison to the Photoshop images provided by 'ZZPot' (<https://github.com/ZZPot/Color-transfer>). As discussed later, the quality of the processed images is somewhat compromised by the poor quality of the raw images.

The images are as follows: - target image, colour source image, standard processed image ($I\alpha\beta$), enhanced processed image ($I\alpha\beta$), Photoshop processed image. The enhanced $I\alpha\beta$ processing corresponds to default settings except that PercentShadingShift is set to 100% (source-image-derived shading) to allow direct comparison to the Photoshop image.





5. Discussion

The images which are subject to processing in Section 4 originate from the following directory.
<https://github.com/ZZPot/Color-transfer/tree/master/images>

The purpose of processing the above images is to allow some sort of cross check with a previous independent analysis. That said the seascape images are problematic. There is clear evidence of a blocking effect due to jpeg artefact. The cross correlation between the ' α ' and ' β ' channels is measured as 0.92 in the target image and 0.90 in the source image.

The purpose of cross correlation processing in the enhanced processing method is to match the cross correlation in the target image to that in the source. In this case however, the two correlation values are already closely matched so it would not be expected that the enhanced processing method would produce much noticeable improvement over the standard processing method. Nevertheless, one could argue that the enhanced $\alpha\beta$ image is slightly more photorealistic particularly in regard to the sun disc and its reflection and the red streaking above the horizon line, but this advantage is marginal.

The jpeg artefact is a real feature of the image and it might be thought that improved suppression of the artefact could indicate a more resilient processing method, on the other hand it could be that improved enhancement of the artefact might indicate that a processing method has greater fidelity. It is not possible to draw a clear conclusion in this regard.

For the lighthouse image the enhanced images look credible. The Photoshop image has whitened cloud to the left of the lighthouse and this feature does not seem to relate too well to the pre-processed target image. The enhanced image is therefore judged to be of better quality.

For the images in Section 1, the enhanced images show improvement over those processed using the standard Reinhard method.