Recovery of Chromaticity Image Free from Shadows via Illumination Invariance

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Abstract

A recent method for recovering a greyscale image that is free from shadow effects is extended such that the recovered image is a colour image, in the sense that 2-dimensional chromaticity information is recovered. First, the effect of lighting change, and thus to a large degree shadowing, is removed by projecting logarithms of 2D colour band-ratio chromaticities into a direction that is independent of lighting change. The resulting 2-vector colour does not contain the contribution of the original lighting in the input image, so this is restored by considering the chromaticity for bright pixels. The resulting image is improved by regression of the chromaticity onto the original image, with promising results.

1. Introduction

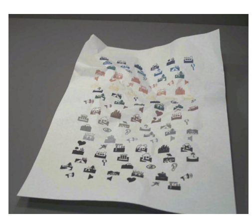
Recently a new image processing procedure was devised for creating an illumination-invariant image from an input colour image [1, 2, 3]. Illumination conditions confound many computer vision algorithms. In particular, shadows in an image can cause segmentation, tracking, or recognition algorithms to fail. An illumination-invariant image is of great utility in a wide range of problems in both computer vision and computer graphics.

An interesting feature of this problem is that *shadows* are approximately but accurately described as a change of lighting. Hence, it is possible to cast the problem of removing shadows from images into an equivalent statement about removing (and possibly later restoring) the effects of lighting in imagery. Although shadow removal is not always perfect, the effect of shadows is so greatly attenuated that many algorithms can easily benefit from the new method; e.g., a shadow-free active contour based tracking method shows that the snake can without difficulty follow an object and not its shadow, using the new approach to illumination colour invariance [4].

In the shadow removal method devised, a 3-band colour image is processed to locate, and subsequently remove shadows. In the original method [1], the output of the algorithm is a greyscale image. Although shadows have been removed, so too has colour. In [3], colour is put back via using the shadow-free image to guide integrating edges from the input colour image. Here, we mean to extend the simpler method [1] from greyscale output to output which is partially colour, in that we recover 2-dimensional colour, along a 1D curve, in the form of *chromaticity* $\boldsymbol{\rho}$, defined as [5]

$$\boldsymbol{\rho} \;=\; \{r, g, b\} \;\equiv\; \{R, G, B\}/(R + G + B) \qquad (1)$$

Although not a full-colour result, as in [3], 2D colour in the form of chromaticity is still useful. To begin with, for a Lambertian surface chromaticity removes shading and intensity from images. That is, a shaded sphere, say, will appear as a disk. This can lead to images that seem somewhat surprising, since they convey colour information only. For example, a crumpled piece of paper in Fig. 1(a), with shading, is reduced to colour-only information in Fig. 1(b). Firstly, since the paper colour, the background, and the black ink all have approximately the same chromaticity (e.g., for $R = G = B$, the chromaticity is {1/3,1/3,1/3}) the black letters recede from our attention; on the other hand, inks that differ only by brightness are now seen as having the same essential colour information.


(a)

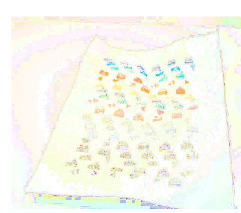

(b)

Figure 1: 3D colour versus 2D chromaticity.

Recovery of the chromaticity is a useful computer vision task, in and of itself, and that is the task we address here. By the definition of chromaticity $\boldsymbol{\rho}$ in eq. (1), we see that the chromaticity is not true colour, but is in fact just 2-dimensional since the components of $\boldsymbol{\rho}$ are not independent:

$$\sum_{k=1}^{3} \rho_k \;=\; 1 \tag{2}$$

Here we mean to extend the illumination invariant image from 1D greyscale, as in [1], to the type of 2D colour image in Fig. 1(b).

The method in [1] is in essence a kind of calibration scheme for a particular colour camera. A camera is calibrated by imaging a (colorful) target, under several different illuminants. An invariant image is derived based on the idea that under Planckian lighting, and for camera sensors that are more or less narrowband (as for an ideal delta-function sensor camera) a 2D scatter plot of the logarithms of ratios R/G versus B/G produce a set of approximately straight lines (this is the case for any model of illumination that changes light colour by exponentiatiation of a power of temperature, T. Each line corresponds to a single patch of the target; each point on a line corresponds to a particular illuminant. For a given camera, all such lines are essentially parallel.

Fig. 2(a) shows log-chromaticities for the 24 surfaces of a Macbeth ColorChecker Chart, (the six neutral patches all belong to the same cluster). If we now vary the lighting and plot median values for each patch, we see the curves in Fig. 2(b). These images were captured using an experimental HP912 Digital Still Camera, modified to generate linear output with no gamma correction. We can see that in fact this straight line hypothesis is indeed essentially carried through in practice. We call the direction of these straight lines the *characteristic direction* for a particular camera. (Note that gamma-correction does not change the the straight line theory [3].)

Consider the image in Fig. 3(a), that includes a region with strong shadowing. Now let us define a set of 2D band-ratio chromaticities, $\boldsymbol{\chi}$, defined via

$$\boldsymbol{\chi} \;=\; \{R/G, B/G\} \tag{3}$$

(as opposed to the L_1-based chromaticities $\boldsymbol{\rho}$ given in eq. (1)). Suppose we denote the 2-vector logarithms of these 2D quantities as $\boldsymbol{\chi}'$:

$$\boldsymbol{\chi}' \;=\; \{\log(R/G), \log(B/G)\} \tag{4}$$

Then if we plot $\boldsymbol{\chi}'$ in a scatter plot, for the image in Fig. 3(a), we obtain the plot Fig. 3(b), with $\boldsymbol{\chi}'$ shown as red points.

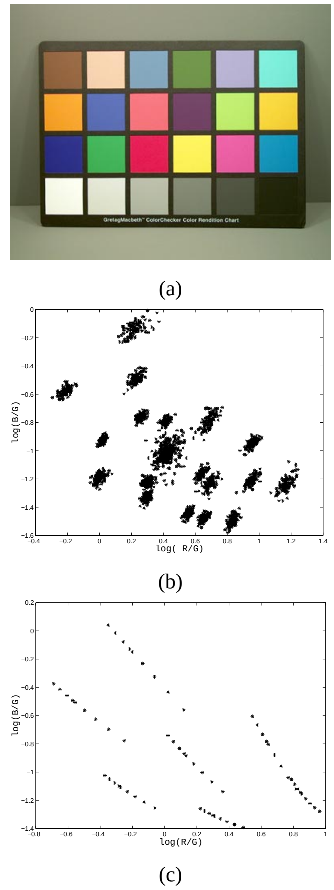
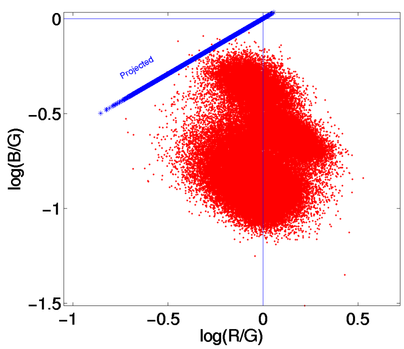


Figure 2: (a): Macbeth ColorChecker Chart image under a Planckian light. (b): Log-chromaticities of the 24 patches. (c): Band-ratio chromaticities for 7 patches, imaged under 14 different Planckian illuminants.

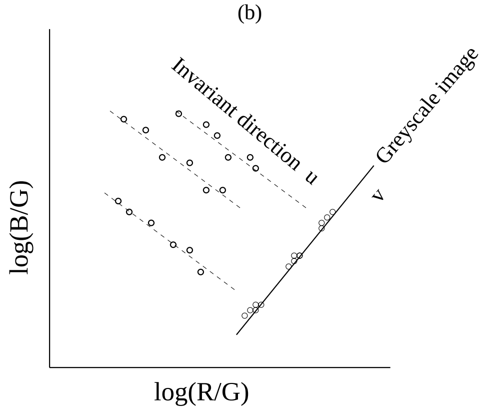
Now the definition of a greyscale, 1D, invariant image is straightforward: suppose the characteristic direction is $\boldsymbol{u}$, on a *calibration* log-log plot such as Fig. 3(c). Then projecting any pixel $\boldsymbol{\chi}'$ onto the orthogonal direction $\boldsymbol{v}$, $\boldsymbol{v} \perp \boldsymbol{u}$, produces a greyscale image which is invariant to the lighting, as illustrated in Fig. 3(c). Fig. 3(b) shows the result of this projection for the real image as the set of blue points projecting onto the $\boldsymbol{v}$ line.

The chromaticity $\boldsymbol{\chi}'$ is seen easily in separate images for each of the two channels in eq. (4). These are shown in Fig. 4(a,b). As well, in Fig. 4(c) the invariant image resulting from projection onto the $\boldsymbol{v}$ direction is shown: we see that indeed the strong shadowing has effectively been removed.

(a)



(b)



(c)

Figure 3: (a): Colour image. (b): Plot of log-chromaticities $\log(R/G)$ versus $\log(B/G)$. (c): Projection orthogonal to camera's characteristic direction produces greyscale image invariant to lighting.

2. Invariant Greyscale Image Formation

Suppose we consider a 3-sensor camera with fairly narrow-band sensors (in [2] we considered 4-sensor cameras, in order to remove not just intensity and shading, but specularities as well.) The spectrum of Planckian illumination is characterized by a single parameter T (temperature). For Lambertian surfaces, and for distant lighting and distant viewing such that orthographic projection is valid, the chromaticity $\boldsymbol{\chi}$ removes both shading and intensity. Let's recapitulate how the linear behaviour of $\boldsymbol{\chi}'$ with lighting change results from the assumptions of Planckian lighting, Lambertian surfaces, and a narrowband camera. Consider the RGB colour $\boldsymbol{R}$ formed at a pixel for illumination with spectral power distribution $E(\lambda)$ impinging on a surface with surface spectral reflectance function $S(\lambda)$. If the three camera sensor sensitivity functions form a set $\boldsymbol{Q}\ (\lambda)$, then we have

$$R_k \;=\; \sigma \int E(\lambda)S(\lambda)Q_k(\lambda)d\lambda\ ,\ \ k = R, G, B\ , \tag{5}$$

where σ is Lambertian shading — surface normal dotted into illumination direction.

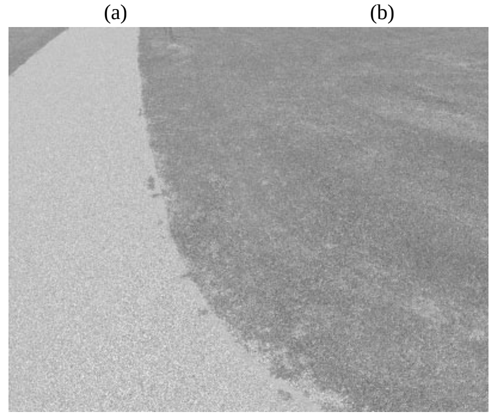
If the camera sensor $Q_k(\lambda)$ is exactly a Dirac delta function $Q_k(\lambda) = q_k\delta(\lambda - \lambda_k)$, then eq. (5) becomes simply

$$R_k \;=\; \sigma\ E(\lambda_k)S(\lambda_k)q_k\ . \tag{6}$$

Now suppose lighting can be approximated by Planck's law, in Wien's approximation [5], for temperature T (reasonable for the range of typical lights 2,500-10,000°K):

(a)

(b)



(c)

Figure 4: (a,b): Band-ratio log chromaticities $\boldsymbol{\chi}'$; (a): $\log(R/G)$; (b): $\log(B/G)$. (c): Invariant image, resulting from projecting $\boldsymbol{\chi}'$ onto the direction orthogonal to the camera's characteristic direction.

$$E(\lambda,T) \simeq I\, c_1 \lambda^{-5} e^{-\frac{c_2}{T\lambda}} . \quad (7)$$

with constants c_1 and c_2. The overall light intensity is I.

In this approximation, from (6) the RGB colour R_k, $k = 1 \ldots 3$, is simply given by

$$R_k = \sigma\, I\, c_1 \lambda_k^{-5} e^{-\frac{c_2}{T\lambda_k}} S(\lambda_k) q_k . \quad (8)$$

Let us now form the band-ratio 2-vector chromaticities $\boldsymbol{\chi}$,

$$\chi_k = R_k / R_p \ , k = 1..2 \quad (9)$$

where p is one of the channels and k indexes over the remaining responses. We could use $p = 2$ (i.e., divide by Green) and so calculate $\chi_1 = R/G$ and $\chi_2 = B/G$, or divide by another channel, or by the geometric mean of R,G,B, $\sqrt[3]{RGB}$ [3]. We see from eq. (8) that forming the chromaticity effectively removes intensity and shading information. If we now form the log of (9), then

$$\chi'_k \equiv \log(\chi_k) = \log(s_k/s_p) + (e_k - e_p)/T , \quad (10)$$

with $s_k \equiv c_1 \lambda_k^{-5} S(\lambda_k) q_k$ and $e_k \equiv -c_2/\lambda_k$. Thus eq. (10) is a straight line parameterized by T. Its equation is

$$\chi_2 - \log(s_2/s_p) = (\chi_1 - \log(s_1/s_p)) \frac{(e_2 - e_p)}{(e_1 - e_p)} . \quad (11)$$

Notice that the 2-vector direction $(e_k - e_p)$ is *independent of the surface*, although the line for a particular surface has an offset that depends on s_k.

The invariant image is that formed by projecting logarithms of chromaticity, χ'_k, $k = 1, 2$, into the direction $\boldsymbol{e}^{\perp}$ orthogonal to the vector $\boldsymbol{e} \equiv (e_k - e_p)$. Vector $\boldsymbol{v}$ in the diagram Fig. 3(c) is now seen to be this direction $\boldsymbol{e}^{\perp}$. The result of projection is a single scalar value $\mathcal{I}'$, and the invariant image results from exponentiation of the result to greyscale $\mathcal{I}$:

$$\begin{aligned} \mathcal{I}' &= \boldsymbol{\chi}' \cdot \boldsymbol{e}^{\perp} , \\ \mathcal{I} &= \exp(\mathcal{I}') . \end{aligned} \quad (12)$$

3. Invariant Chromaticity Image Formation

We now make a simple yet important observation. Consider the blue line of points projected onto the $\boldsymbol{e}^{\perp}$ vector, in Fig. 3(b). While the value $\mathcal{I}'$ along the $\boldsymbol{e}^{\perp}$ line is indeed our looked-for invariant, we have so far neglected the fact that the line of $\boldsymbol{\chi}'$ points in fact does contain colour information. As the blue line extends over log-ratio chromaticity space, the colour of the pixel changes.

All we need to do to visualize this colour change is replace out projection of the 2-vectors onto the $\boldsymbol{e}^{\perp}$ direction by multiplication of the 2-vectors with a 2×2 projector $P_{e^{\perp}}$ that takes chromaticity values $\boldsymbol{e}^{\perp}$ into the 1D direction $\boldsymbol{e}^{\perp}$ but preserves the vector components. That is, we define a colour 2-vector illumination invariant via

$$\begin{aligned} \widetilde{\boldsymbol{\chi}}' &\equiv P_{e^{\perp}} \boldsymbol{\chi}', \\ P_{e^{\perp}} &= \frac{\boldsymbol{e}^{\perp} (\boldsymbol{e}^{\perp})^T}{\| \boldsymbol{e}^{\perp} \|} \end{aligned} \quad (13)$$

The relationship to the original, greyscale image $\mathcal{I}'$ is thus

$$\mathcal{I}' = \widetilde{\boldsymbol{\chi}}' \cdot \boldsymbol{e}^{\perp}$$

Note that when we go back to a correlate of RGB colour — the L_1 normalized chromaticity $\boldsymbol{\rho}$ — the colour along the "Greyscale image" line in Fig. 3(c) changes along the projection line.

However, we do have a problem. From eq. (10), by projecting orthogonal to 2-vector $(e_k - e_p)$ we have effectively removed all lighting from the image, leaving behind what amounts to an intrinsic, reflectance-only based image. The best we hope to do is recover an approximation of the *original image's chromaticity* for pixels outside the shadows, and to do so we must put back some version of the offset in each pixel that we have removed by projection. Fig. 5 shows a simple scheme for carrying out this objective. To

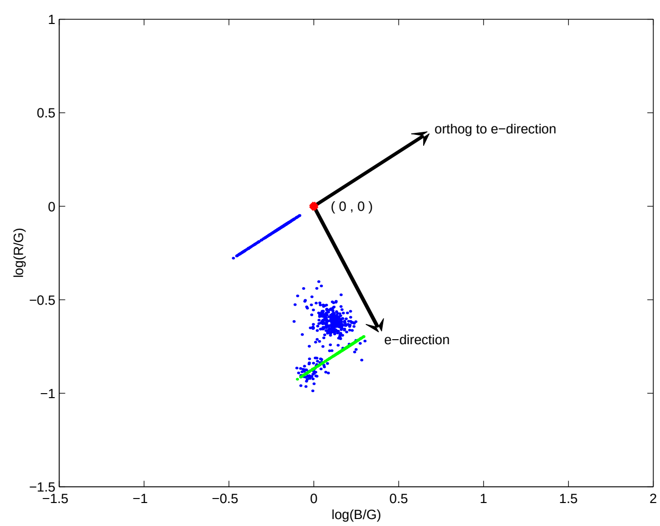


Figure 5: Restoring illumination to projected chromaticities.

begin with, we identify the brightest pixels in the original input colour image, as these are most likely to not be in shade (we used the top 1%, here). Then we add enough of the characteristic direction vector $(e_k - e_p)$ to best match the correct chromaticities of these brightest pixels with the estimated, illumination free, recovered chromaticities $\widetilde{\boldsymbol{\chi}}'$, and then go to exponentiated values:

$$\begin{aligned} \widetilde{\boldsymbol{\chi}}' &\rightarrow \widetilde{\boldsymbol{\chi}}' + \boldsymbol{\chi}'_{extralight} \, , \\ \widetilde{\boldsymbol{\chi}} &= \exp(\widetilde{\boldsymbol{\chi}}') \end{aligned} \tag{14}$$

The diagram shows a few pixels, from outside of shadow regions.

However, since we are accustomed to viewing L_1 chromaticity images, such as Fig. 1(b), we should also go from band-ratio chromaticity $\boldsymbol{\chi}$ back to chromaticity $\boldsymbol{\rho}$. We have from eq. (1) that

$$\begin{aligned} \boldsymbol{\rho} &= \{R, G, B\}/(R + G + B) \\ &= \{\chi_1, 1, \chi_2\}/(\chi_1 + 1 + \chi_2) \end{aligned} \tag{15}$$

so that in fact knowing $\boldsymbol{\chi}$ gives us $\boldsymbol{\rho}$ as well.

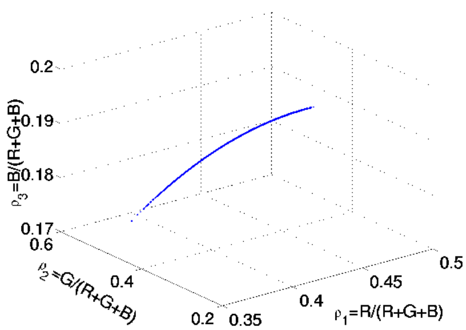


Figure 6: Projection line becomes a curve in L_1 chromaticity space $\boldsymbol{\rho}$.

Fig. 7(b) shows the effect of restoration of an estimate of the 2-vector offset required to put the original image's lighting back into the recovered chromaticity. We see that the suggested method has indeed done quite well, compared to the shadowed, original version Fig. 7(a).

However, the result is still not as accurate as it could possibly be, and in fact we can correct this result by performing a regression of the resulting chromaticity $\boldsymbol{\rho}$ back to the brightest quartile, say, in the original image. To do so, we can transform the chromaticity $\boldsymbol{\rho}$ via a 3×3 matrix $\boldsymbol{M}$ that serves to map these pixels back to values $\boldsymbol{\rho}$ from the input image. Since the result should again be a chromaticity, so that eq. (2) is still obeyed, we should use a constrained optimization such that the sum of each column $\boldsymbol{M}_i$ of $\boldsymbol{M}$ is unity; as well, since the range of any chromaticity $\boldsymbol{\rho}$ is [0,1], elements of matrix $\boldsymbol{M}$ should also be constrained to lie in this interval.

An optimization of this type is as follows:

$$min \; \sum(\boldsymbol{\rho}_{\text{orig, brightest quartile}} - \boldsymbol{M} \, \widetilde{\boldsymbol{\rho}} \,)^2$$

$$\text{with constraints} \begin{cases} \sum \boldsymbol{M}_i = 1, \; i = 1..3, \\ \text{convex sum} \\ \\ 0 \leq \boldsymbol{M} \leq 1 \\ \text{range of chromaticity} \end{cases} \tag{16}$$

The result of this additional step on the image in Fig. 7(b) is shown in Fig. 7(c). While we cannot easily obtain an error value for the chromaticity in this resulting image, since we are really concerned with both non-shadowed and shadowed pixels and we do not have ground truth for the latter, nevertheless clearly the colour of pixels is closer to the correct colour in non-shadowed pixels in the original image, especially in the colour of the footpath in the image. The rms error for the non-shadowed regions, the high-brightness pixels, is always reduced by the algorithm by about 50% as a result of the regression step. Fig. 6 shows how the projection line in Fig. 3(b) becomes a curve, after the transform back to L_1 chromaticity $\boldsymbol{\rho}$ given by eq. (15).

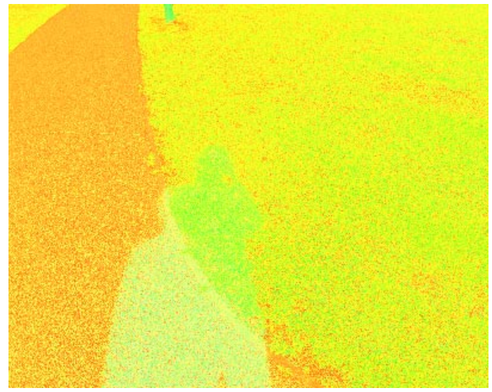
Figs. 8 and Figs. 9 show more results, using the above procedure. Clearly, the method does show usefulness since an approximation of correct chromaticity is indeed seen to be recovered.

In Fig. 8, the input image has a large shadow area, and this is effectively removed by the method. As well, the recovered chromaticity quite well approximates the correct chromaticity for non-shadowed regions. For example, in Fig. 8(c), the chromaticity of the sky colour is actually very close to that in Fig. 8(b) — this is not apparent to the eye unless one crops the region of interest out of the image, because of the simultaneous contrast effect in human vision.

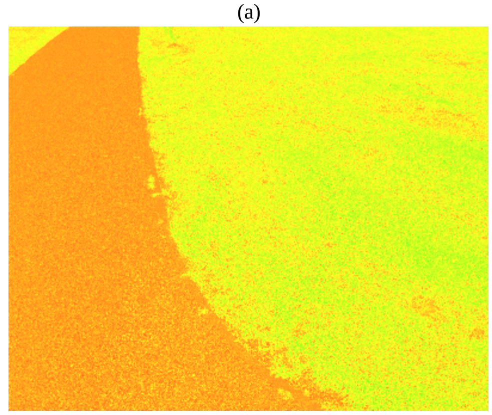
As well, if we apply the algorithm to a general input image, as in Fig. 9, one that has incidental shadows but is not a shadow test *per se*, we see that the algorithm does indeed recover an approximation of shadow-free chromaticity.

4. Conclusions

We have set out and demonstrated a method for recovering an image in 2D colour that is invariant to lighting change, and hence more or less resistant to shadowing effects, extending previous methods from the recovery of a greyscale image to the recovery of shadow-free chromaticity images. The method consists of using all the information contained in the projection of the image into the lighting direction, and thus retaining 2D colour, followed by carefully restoring lighting to the image so as to best match the original. Results are seen to be promising. However, one area not addressed so far is how well the method performs in the face of blocking effects due to JPEG artifacts. As well, we are of course also interested in applying the method to unsourced images from uncalibrated sources. We shall pursue these research directions elsewhere.



(a)



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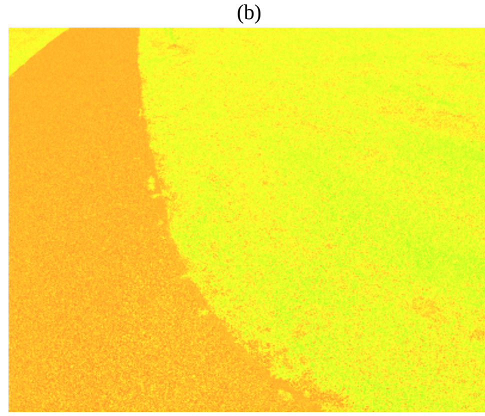

(c)

Figure 7: (a): Original chromaticity for input colour image. (b): Result of projection followed by restoration of characteristic direction contribution derived from bright pixels. (c): Correction by regression of restored chromaticity to first quartile of original image.

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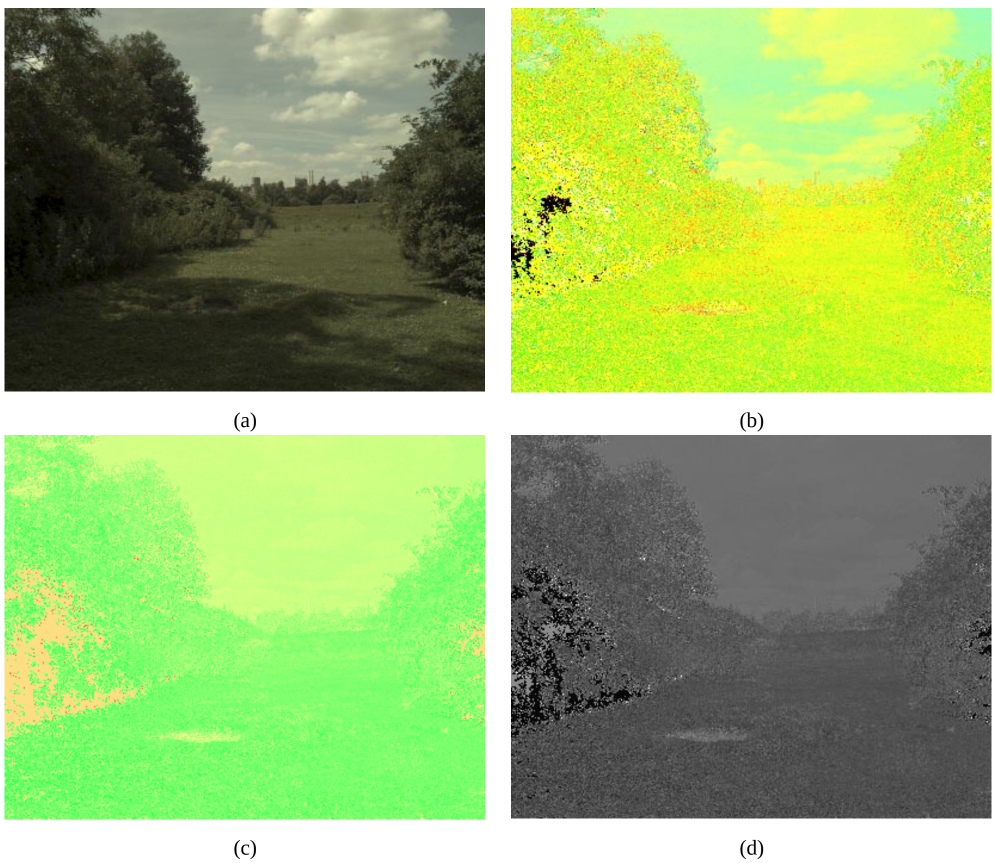

Figure 8: (a): Input colour image. (b): Chromaticity for input colour image, including chromaticity in shadowed regions. (c): Result of projection and restoration of light, plus regression. The chromaticity of the sky region, for example, is close to the correct value. (d): Greyscale invariant.

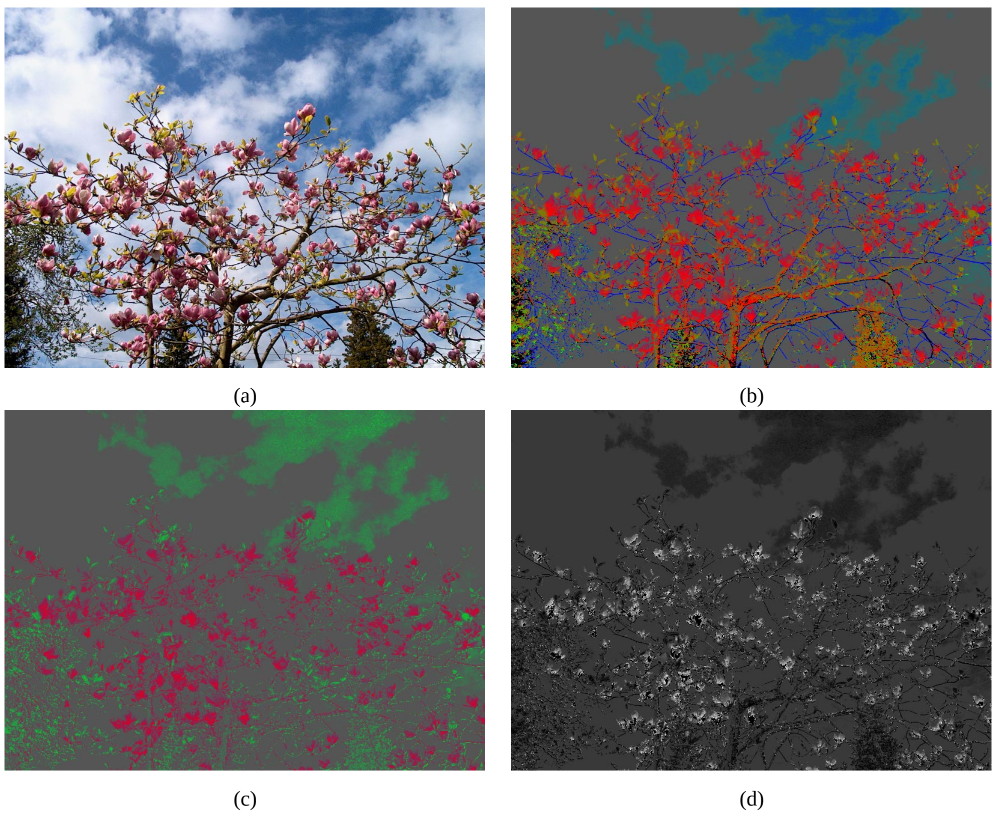

Figure 9: Use of the algorithm on general input. (a): Input colour image. (b): Original chromaticity for input colour image. (c): Result of projection and restoration of light, plus regression. (d): Greyscale invariant.