

# Illumination Intensity, Object Geometry and Highlights Invariance in Multispectral Imaging\*

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**Abstract.** It is well-known that image pixel values of an object could vary if the lighting conditions change. Some common factors that produce changes in the pixels values are due to the viewing and the illumination direction, the surface orientation and the type of surface.

For the last years, different works have addressed that problem, proposing invariant representations to the previous factors for colour images, mainly to shadows and highlights. However, there is a lack of studies about invariant representations for multispectral images, mainly in the case of invariants to highlights.

In this paper, a new invariant representation to illumination intensity, object geometry and highlights for multispectral images is presented. The dichromatic reflection model is used as physical model of the colour formation process. Experiments with real images are also presented to show the performance of our approach.

## 1 Introduction

The image pixel values of an object could vary if the lighting conditions change. During the image formation process, the main factors that could produce changes in the pixel values are: viewing direction, surface orientation, highlights, illumination direction, illumination intensity, illumination colour and inter-reflections.

The aim of invariant image representations is to obtain the same value for the pixels of an object, independently of the conditions commented above. These representations can be quite useful to measure or recognize objects in images or other tasks that require invariance to any of these properties. For instance, intensity-based edge detectors cannot distinguish the physical cause of an edge, such as material, shadows, surface orientation changes, etc. This fact produces poor segmentations and, therefore, bad recognition of objects.

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For the last years, significant works about invariant representations for colour images have been carried out [2], [4], [1]. Many of them use the reflection model introduced by Shafer in [7] as a physical model to understand the colour of a concrete pixel. The reader is addressed to [3] for a comprehensive study.

The next section explains how to obtain invariant representations to illumination intensity and other geometric factors (as shadows) and highlights, performing simple mathematical operation with bands (R, G and B, for colour images). Our approach for multispectral images is based on similar properties, taking advantage of the Neutral Interface Reflection (NIR) and narrow band filter assumptions. We have named our invariant  $L_n$  which is invariant to illumination intensity (assuming white illumination), object geometry and highlights while approximately preserving the spectral information of the image.

## 2 Multispectral Invariant Representations

The use of the reflection model is key point to understand how a sensor works. The Dichromatic reflection model introduced by [7], represents the output value  $C$  of a pixel in the image plane as:

$$C_n = m_b(\vec{n}, \vec{s}) \int_{\lambda} f_n(\lambda) e(\lambda) c_b(\lambda) d\lambda + m_s(\vec{n}, \vec{s}, \vec{v}) \int_{\lambda} f_n(\lambda) e(\lambda) c_s(\lambda) d\lambda \quad (1)$$

for  $C_n = \{C_1, \dots, C_N\}$  giving the  $C_{th}$  sensor response of a multispectral camera,  $c_b$  and  $c_s$  are the surface albedo and Fresnel reflectance respectively,  $\lambda$  denotes the wavelength,  $\vec{n}$  is the surface patch normal,  $\vec{s}$  is the direction of the illumination source and  $\vec{v}$  is the direction of the viewer. Geometric terms  $m_b$  and  $m_s$  denote the geometric dependencies on the body and surface reflection component respectively.

Considering the Neutral Interface Reflection (NIR) model (assuming that  $c_s(\lambda)$  has a constant value independent of the wavelength), narrow band filters modelled as a unit impulse and white illumination (equal energy density for all wavelengths within the visible spectrum), then  $e(\lambda) = e$ ,  $f = \int_{\lambda} f_1(\lambda) d\lambda = \dots = \int_{\lambda} f_N(\lambda) d\lambda$  and  $c_s(\lambda) = c_s$ , and hence being constants. Then, with this assumption, the measured sensor values are given by:

$$C_n = e m_b(\vec{n}, \vec{s}) K_n + e m_s(\vec{n}, \vec{s}, \vec{v}) c_s f \quad (2)$$

with  $K_n = \int_{\lambda} f_n(\lambda) c_b(\lambda) d\lambda$ .

If the object is matte, that is, if it does not have highlights, then the second part of the equation 2 can be neglected. Therefore, the equation 2 can be simplified as follows:

$$C_n = e m_b(\vec{n}, \vec{s}) K_n \quad (3)$$

It is possible to obtain invariant representations to some conditions, performing simple mathematic operations with the bands. For instance: for matte objects, dividing two bands  $i, j$  allows to get an illumination intensity and object geometry invariant representation, i.e. non-dependent of  $m_b$  and  $e$  factors:

$$\frac{C_i}{C_j} = \frac{em_b(\vec{n}, \vec{s})K_i}{em_b(\vec{n}, \vec{s})K_j} = \frac{K_i}{K_j} \quad (4)$$

For shiny objects, subtracting one band from another provides a highlights invariant representation, i.e. invariant to viewpoint  $m_s$  and specular reflection coefficient  $c_s$ :

$$\begin{aligned} C_i - C_j &= (em_b(\vec{n}, \vec{s})K_i + em_s(\vec{n}, \vec{s}, \vec{v})c_s f) \\ &\quad - (em_b(\vec{n}, \vec{s})K_j + em_s(\vec{n}, \vec{s}, \vec{v})c_s f) \\ &= em_b(\vec{n}, \vec{s})(K_i - K_j) \end{aligned} \quad (5)$$

Finally, first subtracting and then dividing bands provides a representation invariant to highlights, illumination intensity and object geometry:

$$\frac{C_i - C_j}{C_k - C_l} = \frac{em_b(\vec{n}, \vec{s})(K_i - K_j)}{em_b(\vec{n}, \vec{s})(K_k - K_l)} = \frac{K_i - K_j}{K_k - K_l} \quad (6)$$

Following these ideas, Stockman and Gevers [8] presented two invariant representation for multispectral images, the normalized hyper-spectra and the hyper-spectral hue.

The normalized hyper-spectra is a representation invariant to  $e$  and  $m_b$  factor. It is defined as follows:

$$c_n = \frac{C_n}{C_1 + \dots + C_N} \quad (7)$$

The calculation of the hyper-spectral hue needs a special attention since hue orders colors in a circular way. First an equal-energy illumination is obtained dividing each band by the corresponding sensor response of a white reference object, and supposing that the filter is a narrow band filter modelled as a unit impulse [8]. Thus, the object can be made independent of the illumination intensity.

In a second step, all the values are transformed as follows:

$$c_n = C_n - \min(C_1 + \dots + C_N) \quad (8)$$

As a result, the transformed spectrum is invariant to highlights.

After the pre-processing of the spectrum, the hue can be calculated using the following equation:

$$H(c_1, \dots, c_N) = \arctan \left( \frac{\sum_i c_i \cos(\alpha_i)}{\sum_i c_i \sin(\alpha_i)} \right), \text{ where } \alpha_i = \frac{(i-1)2\pi}{N} \quad (9)$$

As a result, the transformed spectrum is also invariant to object geometry. The reader is addressed to [8] for further details.

### 3 $L_n$ Multispectral Invariant

The multispectral Hue is invariant to illumination intensity (assuming white illumination), object geometry and highlights which are the properties that we

are looking for. Nevertheless, the fact that it transforms an image with  $N$  bands to an image with just 1 band can produce an import loose of multispectral information, which can be crucial in many applications.

Therefore, we propose the  $L_n$  invariant for multispectral images which transforms an image with  $N$  bands into an invariant representation with  $N - 2$  independent bands. It is defined as follows:

$$L_n = \frac{C_n - \min(C_1, \dots, C_N)}{\sum_j (C_j - \min(C_1, \dots, C_N))} \quad (10)$$

In order to make the acquired images independent from illumination, the aperture times of our multispectral camera have been calculated carefully for every band to eliminate differences in light intensity that are caused by the spectrum characteristics of the lamps, the filter and the sensor. This calculation is done by repeatedly taking multispectral images of a white reference, (i.e. a white surface with equal reflection properties in a wide spectrum) and adjusting the aperture times until the light intensity is the same in every band. This process is called white balancing. These aperture times compensate for the unknown spectral characteristics of the lamps, the filter and the sensor. Thanks to that process, we can assume that we are using white illumination and therefore the acquired images fulfill that  $e(\lambda) = e, \forall \lambda$ . This fact allows to suppose that the sensor behaviors following Equation 2.

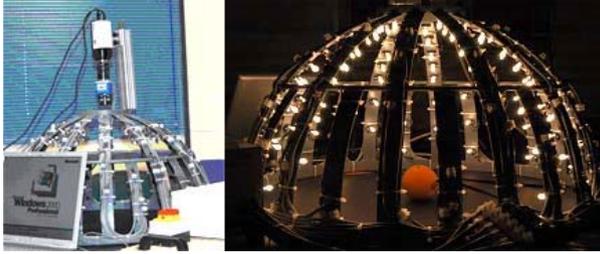
The aim is to obtain an invariant representation where the spectral information is preserved, i.e. the invariant pixel value not to be a mixture of other pixel (wavelengths) values. Lets,  $C_i = em_b K_i + B$ ,  $C_j = em_b K_j + B$  and  $\min(C_1, \dots, C_N) = C_{min} = em_b K_{min} + B$ , with  $B = em_s c_s f$  being a constant value along  $\lambda$ ,  $m_b = m_b(\vec{n}, \vec{s})$  and  $m_s = m_s(\vec{n}, \vec{s}, \vec{v})$ . In order to achieve highlights invariance, we can perform  $C_i - C_j$ , but then, a mixture of body reflectance values from both pixels is obtained as an invariant, losing spectral information,  $C_i - C_j = em_b(K_i - K_j)$ . However, using the minimum value, the spectral information is approximately preserved, since  $C_{min} = em_b K_{min} + B \simeq B$  and therefore  $C_i - C_{min} \simeq em_b K_i + B - B = em_b K_i$ , i.e. invariant to highlights. In addition,  $L_n$  is also invariant to  $e$  and  $m_b$ , i.e. illumination intensity and geometry factors, since:

$$L_n \simeq \frac{em_b K_n}{\sum_j em_b K_j} = \frac{K_n}{\sum_j K_j} \quad (11)$$

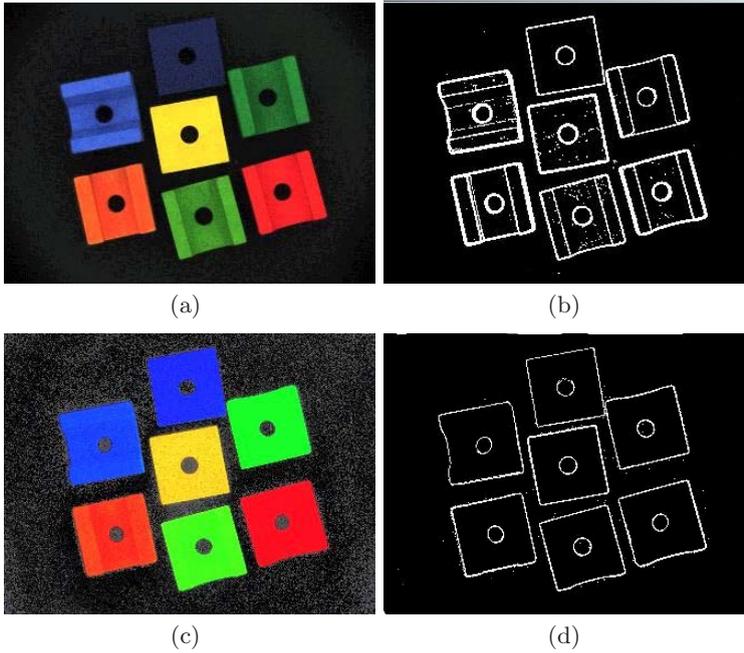
Note that we are dividing all the pixel values by a constant, therefore the spectral information is maintained.

## 4 Experimental Results

In order to test our approach in real images, a set of multispectral images have been taken using a specially designed illumination chamber (see Figure 1). The chamber is a perfect hemisphere with a large number of low-voltage halogen lamps attached on the inside uniformly distributed through the hemisphere. The



**Fig. 1.** Illumination chamber used to capture our multispectral images

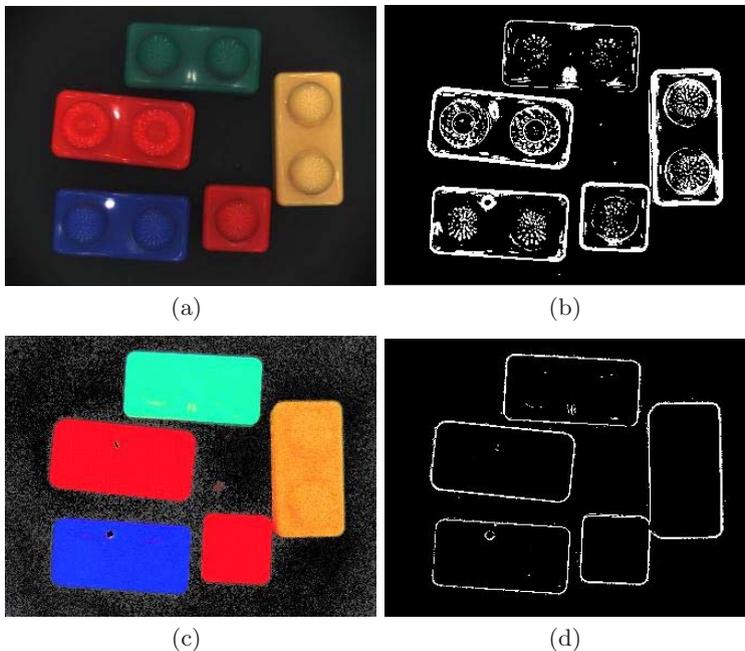


**Fig. 2.** Wooden toys experiment. (a) original image, (b) original edge-image, (c)  $L_n$  invariant representation, (d)  $L_n$  invariant edge-image. See text for explanation

lamps illuminate the object from all sides and from equal distances, minimizing shadows, shine and other effects. For each image, 33 bands have been captured, from  $400nm$  to  $720nm$ , using a bandwidth of  $10nm$ .

From the experiments performed using the set of images captured, the most significative ones are reported in this paper. Children toys have been selected as test objects since they have interesting properties that help us to demonstrate the invariant behaviour of our approach.

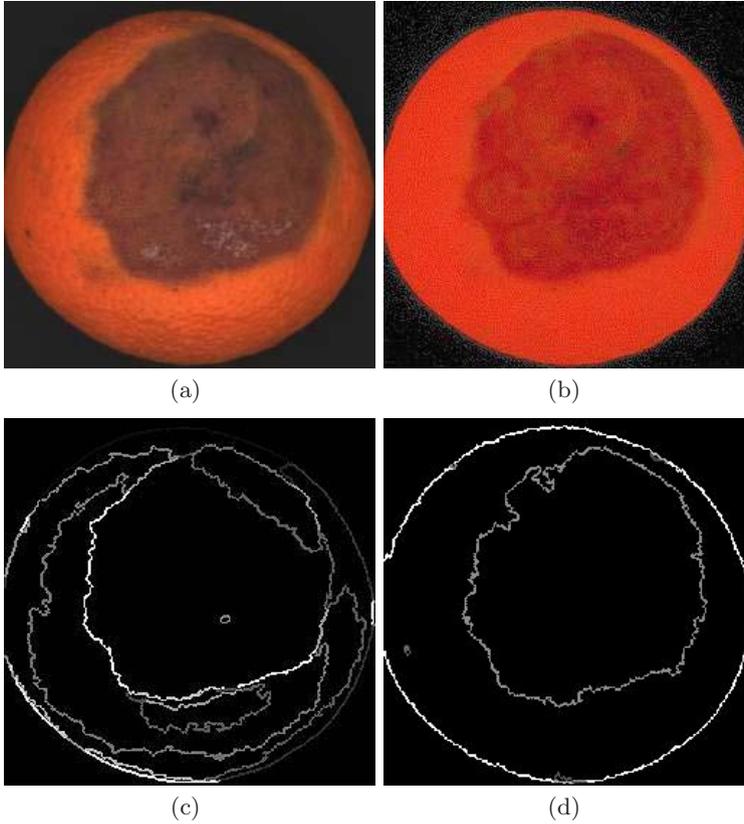
Figure 2 shows the "wooden toys" experiment. In figure 2a, the original 33-bands image is presented. In order to show the image as a RGB image, the bands  $650nm$ ,  $540nm$ ,  $490nm$  have been selected to be the R, G and B chan-



**Fig. 3.** Plastic Toys experiment. (a) original image, (b) original edge-image, (c)  $L_n$  invariant representation, (d)  $L_n$  invariant edge-image. See text for explanation

nels, respectively. Figure 2b shows the edge-image obtained from the 33 band original image. White pixels are the ones that are greater than a threshold in the multispectral gradient of the image. The gradient of the multispectral image has been calculated using the *Di Zenzo* multispectral gradient [9]. Note the edges produced by shadows in the objects. Figure 2c and 2d show the results of our approach. Figure 2c shows the  $L_n$  invariant representation as a RGB image ( $R = 650nm$ ,  $G = 540nm$  and  $B = 490nm$ ). Finally, Figure 2d shows the edge image obtained from the transformed multispectral image. Note that the effect of the shadows has been completely eliminated.

The next experiment involves plastic toys whose reflection properties produce highlights, which are hard to remove. Figure 3a shows the original image. As in the previous experiment, the bands  $650nm$ ,  $540nm$ ,  $490nm$  have been selected as the R, G and B channels, respectively. Figure 3b shows the edge-image obtained from the 33 band original image. Note the edges produced by shadows and highlights. Figure 3c shows the results of our invariant as a RGB image ( $R = 650nm$ ,  $G = 540nm$  and  $B = 490nm$ ). Finally, 3d shows the edge image obtained from the invariant image. Note that the effect of the shadows has been completely eliminated and the effect of the highlights has been almost completely eliminated. The brightest points have not been suppressed because of sensor saturation at these pixels.



**Fig. 4.** Orange segmentation experiment. (a) original image, (b)  $L_n$  invariant representation, (c) segmentation results of original image, (d) segmentation results of the transformed (by the invariant) image

In last experiment, our approach has been tested in an application to segment orange fruits. Figure 4a shows the original image as a RGB ( $R = 650nm$ ,  $G = 540nm$  and  $B = 490nm$ ). In spite of our effort to make an illumination chamber with a homogeneous illumination, the image of the orange shows variable illumination in different areas of the orange, higher in the center than in the periphery. Figure 4b shows the invariant representation, note that the illumination problems have been drastically reduced. In order to test if the invariant representation improves the segmentation of the orange, a multispectral segmentation algorithm has been used (see [6], [5]), using as input the original (Figure 4a) and the transformed image (Figure 4b). Figure 4c and 4d show both results.

Note the poor results of the segmentation using the original image due to the problems with illumination effects. On the other hand, note the excellent results of the segmentation process in Figure 4d, where the effect of the illumination problems have not influenced the extraction of the regions of the orange.

## 5 Conclusions

A new invariant for multispectral images has been presented in this paper. Our approach transforms the image into a new space which is invariant to illumination intensity (assuming white illumination), object geometry and highlights while approximately preserving the spectral information of the image.

The presented method has been successfully tested in real multispectral images with shadows and strong highlights, where it has been demonstrated the ability of the invariant to deal with those effects in the image and, therefore, can be used as input of other image processing applications, for instance, segmentation.

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