

# ***High Dynamic Range Multispectral VIS+NIR Imaging Techniques for Out-of-the-Lab Scenes***

*Miguel Ángel Martínez Domingo*

*Color Imaging Laboratory, Department of Optics, Faculty of Sciences, University of Granada, Spain.*

[martinezm@ugr.es](mailto:martinezm@ugr.es)

**Abstract:** *Digital imaging is a tool with a great potential for scientific applications. Such applications usually are carried out under controlled imaging conditions. This means that all, or at least the most important parameters involved in the imaging process (e.g. illumination angle, intensity and spectrum, geometry, perspective, processing time, motion...) can remain within a known range of values. However, sometimes some applications can not be carried out under controlled laboratory conditions. In these cases, some advanced imaging techniques must be applied in order to overcome the intrinsic limitations of imaging devices. We study the case of urban outdoors scenes, in which we want to automatically segment the singular objects present on them such as cars, ground, buildings, pedestrians, plants, etc. We propose the design of a High Dynamic Range MultiSpectral Imaging Device (HDRMS) operating in the spectral range from 400nm to 1000nm (Visible + Near Infra Red or VIS+NIR).*

## **1. Multispectral techniques (VIS+NIR)**

Common digital cameras respond to roughly three wide spectral ranges in the visible (red, green and blue). If we increase the number of spectral channels narrowing them down, we can retrieve more detailed spectral information about the objects present in the scene. Besides, if we include channels covering the NIR range up to 1000nm, it would help us to identify some objects like plants (e.g. via vegetation index calculation) [1]. In general, if we characterize spectrally the objects that are expected to appear in the scenes that our application will cover, we can find that some spectral bands (or a combination of them) are usually enough to identify and classify the different object classes present on them. Since we are aiming for a general purpose application imaging urban scenes, we have chosen relatively narrow spectral channels covering the range from 400nm to 1000nm with certain overlap (to avoid leaving some spectral regions uncovered by the sensors' spectral response range).

Nevertheless, apart from the task of identifying which spectral channels to choose for our application, multispectral imaging brings other important limitations specially when we are under uncontrolled imaging conditions. Capturing time is one of the critical aspects of it. Usually for capturing the different spectral bands, multispectral imaging devices scan spatially [2] or spectrally [3] the scene. This process takes time and in uncontrolled conditions, time is an enemy to fight against. Changes in illumination, geometry or moving objects, are specially unfortunate when happening during the capture. We usually end up with a spectral image, in which sensor responses in a specific pixel coordinate, correspond to different objects or areas for the different

spectral bands (producing effects like ghosting, blur, inaccurate image registration, etc).

In order to overcome these issues, we have proposed a theoretical design based on simulations of a pseudo-snap-shot multispectral system based on a new sensor technology that is still under development. The new sensor architecture is called Transverse Field Detectors (TFD). In these sensors, the photons from different spectral channels are collected at different depths in the silicon layer [4]. They take advantage of the wavelength-dependent penetration depth of photons in silicon. Besides, applying a tunable transverse electric field, we can modify these depths, and therefore we can tune the sensitivities of the sensor matrix electronically and very fast. If we combine this filter-less technology with a Color Filter Array (CFA), we can get up to 36 spectral channels in two consecutive shots. Figure 1 shows a comparison scheme between a normal Bayer pattern filtered RGB digital camera (top) and the proposed system (bottom). The details of the design are explained in [5].

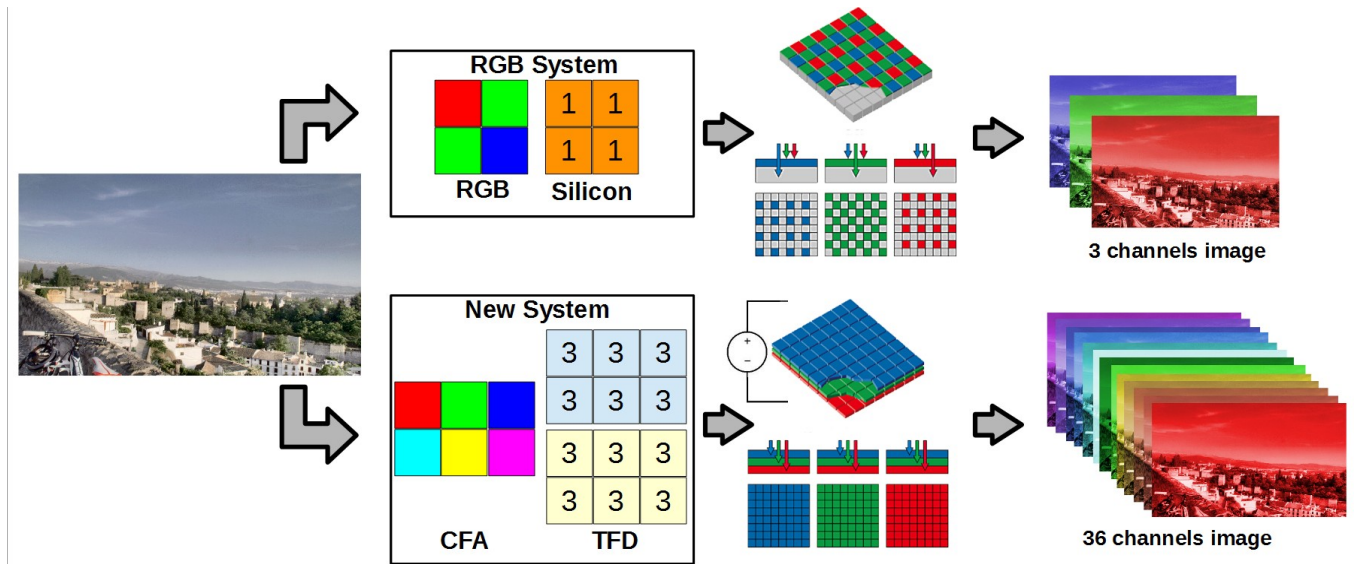


Figure 1: Schematic comparison between RGB-Bayer color camera and our proposed system.

Including the CFA in the design, we are trading off spatial resolution in order to gain a higher number of spectral channels in the final image. The total exposure time will depend of course on the imaging conditions (amount of light on the scene), but tuning the bias transverse voltage applied will happen in milliseconds. In table 1, we can see the color and spectral error metrics used to assess the performance in a spectral estimation task of the proposed system, against those of non-TFD based system using the same kind of CFA. The spectral estimation was done in a 10-folds cross validation using 1700 reflectances from Natural Color System (NCS) and regularized polynomial kernel regression.

System	$\Delta E_{00}$	GFC	RMSE
TFD+CFA	0.23	0.9997	0.0064
NON-TFD+CFA	1.26	0.9992	0.0094

Table 1: Error metrics of the proposed system and a non-TFD based system.

## 2. High Dynamic Range techniques (HDR)

Whenever we are going to capture an image of any kind, we need to adjust some parameters in our camera. A very important parameter is the exposure, which is usually controlled by either adjusting the exposure time, the aperture or (in digital cameras) the ISO speed of the sensor. Outdoors scenes usually present a very high range of light intensities [6]. However, common image sensor architectures are able to capture only a low dynamic range in a single shot. Some authors have proposed new sensor architectures to increase the dynamic range of images in a single shot [7,8]. Including multiple sensors on our Multispectral system would increase the cost of the device, and adding a new layer of filters on top of the existing one would reduce even more the spatial resolution of the final image. We have considered the option of taking multiple shots with different exposure settings (which is firmware applicable to any imaging camera). We decided to use as free parameter the exposure time, since different apertures would affect the focus (depth of field) and different ISO speeds would affect the noise, specially for dark image areas. In the previous section we talked about the problem of scanning spatially or spectrally the scene to get the spectral information, and now we are proposing to scan the scene in exposure to get high dynamic range image data. The purpose is to get all pixels of the image (or at least from our region of interest or ROI) properly exposed (neither saturated nor underexposed) in at least one of the exposures captured. For this aim, we have proposed an algorithm based on cumulative histograms and the Camera Response Function of the camera (CRF) [9]. Our algorithm estimates the exposure times needed in order to complete the lost information in a HDR image. Moreover, it does so in such a way that no extra exposures are needed for the estimation. Only the necessary exposures are captured and the whole capture is done sequentially and fast (of course depending on the exposure times needed to cover the ROI dynamic range). The only inputs for the algorithm are the CRF of the camera (which can be easily computed using the method explained in [9]), and a first image captured with a known exposure time, in which at least some pixels of our ROI are well exposed. The details of this algorithm are explained in [10].

In figure 2, we can see the result of the algorithm if we wanted to recover the pixel information of the whole scene (taking into account the camera limitations; it can be seen that the area of the sun is saturated even for the shortest exposure time available). On the left side we see the input image captured with the auto-exposure setting of a Canon EOS 7D camera (middle one), and its cumulative histogram. The other two images are the ones needed to recover the whole dynamic range of the scene, one longer (on the right) and one shorter (on the left) exposure time.

The whole capture is automatic and we can tune some parameters in the algorithm to decide the percentage of pixel population we can afford to lose (saturated or underexposed), as well as the balance between amount of exposures and Signal to Noise Ratio (SNR) of the final HDR image. The algorithm can be used for any imaging device and it would be useful for many applications, not only outdoors scenes, but, in general, any scene condition that requires HDR images (quality control in industry, remote sensing, surveillance, etc).

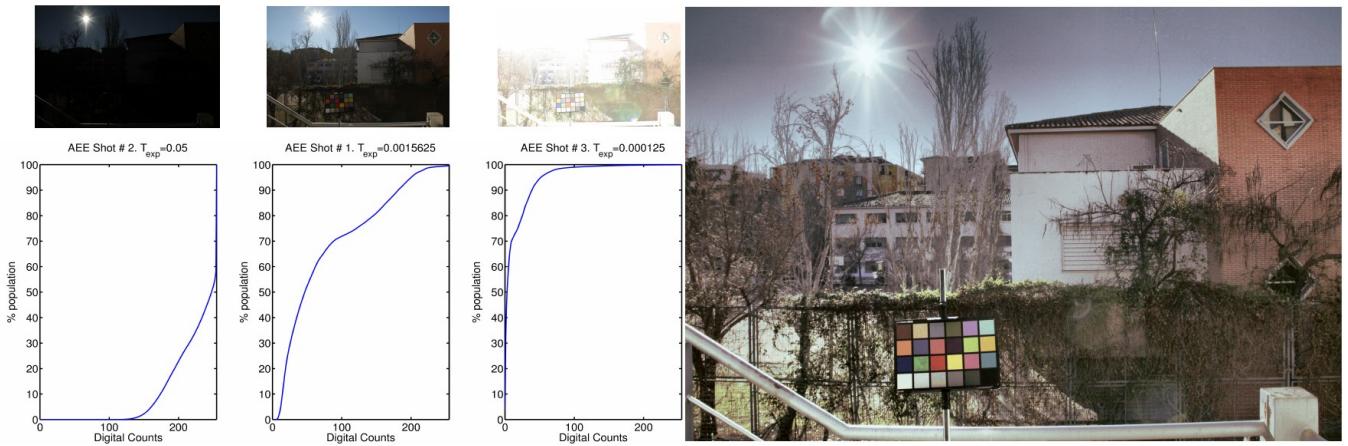


Figure 2: LDR images captured (top left) with their cumulative histograms (bottom left) and tonemapped HDR resulting image (right). Exposure times are expressed in seconds.

### 3. Future work

We are currently studying the effect of veiling glare and lens flare in HDR imaging. When we want to recover a HDR radiance map of the scene using our camera, it is not enough to use techniques such as the CRF, to map sensor responses to exposure (and compute the radiance map discounting the exposure time [9]). It has been demonstrated that the way the camera responds to light depends on the content of the scene. Therefore, for different scenes where the lighting conditions are different, specially for HDR scenes with very bright and very dark areas, the CRF of the camera is different [11]. This is a problem if we try to use our camera as an imaging radiometer, for color or spectral images. We are studying the limits under which we can still recover a usable integrated radiance map from sensor responses using a camera CRF.

Since our final aim is to segment images, we will continue studying which pixel value-space is more convenient for this task. We want to compare LDR raw sensor responses, HDR radiance map values, estimated spectral reflectances or radiances from sensor responses, and we would also like to include in our comparison study some illuminant invariant images. Some authors have proposed multispectral illuminant invariant images, in which the effect of different illumination for different areas of the image is reduced, or eliminated [12]. We believe these techniques would increase the performance of the image segmentation, since the sensor responses of different parts of the same object, under different illuminations, would present similar pixel values, disregarding the spectrum and radiance level of the illumination impinging on them.

Since the TFD technology is still under development and there are only prototype sensors built, we needed to chose a different multispectral imaging system. We opted for a filter-wheel camera. This system belongs to the spectral scanning devices commented in section 1. It is a monochrome camera synchronized with an 8 slots filter wheel. We purchased two sets of 8 filters covering the range from 400 nm to 1000 nm.

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