Spectral unmixing of light-emitting diode and high-intensity discharge illumination sources

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***Abstract*—In the recent decades, high-intensity discharge lamps, installed for public illumination, are gradually being replaced with solid-state lighting (white light-emitting diodes). This is resulting in markedly better energy efficiency, but is also raising environmental concerns related to the extra blue light emitted.**

Using a CubeSat, we plan to track the global progress of solid-state lighting and its contribution to light pollution. Inasmuch as the light emitted from the Earth is a mixture of a wide variety of light sources, estimating the contribution of any individual source is a challenging task referred to as spectral unmixing. In this work, we present a method for spectral unmixing of light mixtures created by a multiplicity of conventional sources, including high-intensity discharge lamps and light-emitting diodes, as measured by a spectraphotometer. We demonstrate unmixing of light into two constituent spectra, one of which is the solid-state lighting spectra, using a non-negative constrained least-squares method with final accuracy of 93%. We furthermore show that the proposed method can be used when the mixture is captured using less than ten filtered detectors rather than a several-thousand-channel spectraphotometer, which is the most likely implementation on our satellite. All of our experiments have been done in a laboratory.

***Index Terms*—Remote sensing, spectroscopy, light emitting diodes, high intensity discharge lamps.**

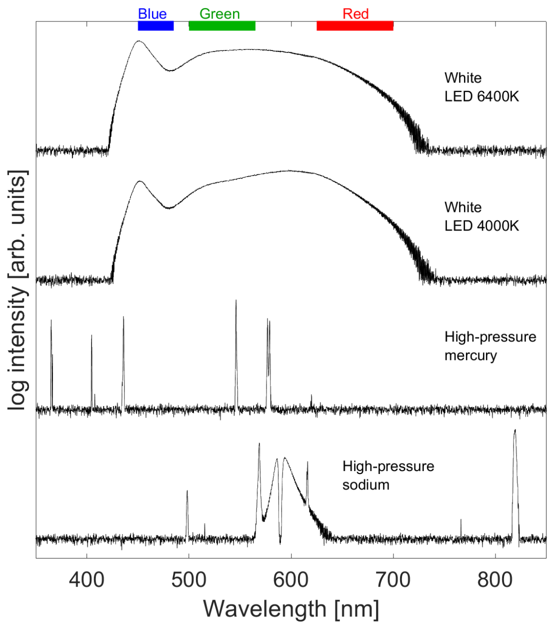


Figure 1: Measured spectra data of white light-emitting diodes and high-pressure sodium and mercury lamps, used in lighting applications and also used in this work.

I. Introduction

Current imaging systems depend on high spatial and spectral resolution to discriminate the types of light sources used for outdoor and public illumination [1]. In recent decades, high-intensity discharge (HID): mercury, sodium, and metal-halide lamps, are gradually being replaced by more energy-efficient solid-state lighting (white light-emitting diodes). A subtle, but important consequence of this migration is that there has been progressively more blue light emitted into the night sky and the surroundings. This is because "white" light-emitting diodes (LEDs) emit significantly more light in the blue part of the spectrum than any other conventional illumination source (Fig. 1). Exposure to blue light during the night disrupts the circadian rhythm in humans and animals and commonly leads to insomnia, stress, and increased risk from a wide range of medical maladies [2]. For these reasons, interest in light pollution has been growing in recent years. Presently, light pollution data measured from space is freely accessible on the internet [3], but this data provides only the emission in the 500 - 900 nm wavelength range and shows no indication of the type of light source that caused the pollution. To explore the ramifications of the new lighting revolution, scientists are missing what could possibly be vital data for linking its effects on human life and nature.

Nighttime remote sensing is in a stage of rapid development [1]. The main challenge of taking data is low light levels emitted, with top-of-atmosphere radiance reaching as low as a few $\mathrm{nWcm^{-1}sr^{-1}\mu m^{-1}}$ [4]. High spatial resolution and multispectral sensors, covering the range from blue to near-infrared light, allow for effective identification of lighting technologies, mapping urban functions, and monitoring energy use [1]. High spatial resolution instruments consist of thousands of small pixels and require large area lenses to measure the faint nighttime light. This increases the cost, weight and size and is generally prohibitive for nano-satellites. Furthermore, multispectral features introduce additional complexity and cost to remote sensing imaging system.

In this work we propose to measure the total light radiated from the surface of the Earth into space, and find the fraction of LED versus HID light sources using a low-cost low-spatial resolution detection system, which uses several single pixel detectors.

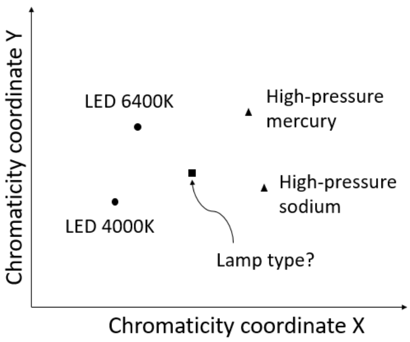


Figure 2: Chromaticity diagram of different illumination sources formed from RGB camera data. Note that these are not actual measured data points, but rather an illustration of the idea.

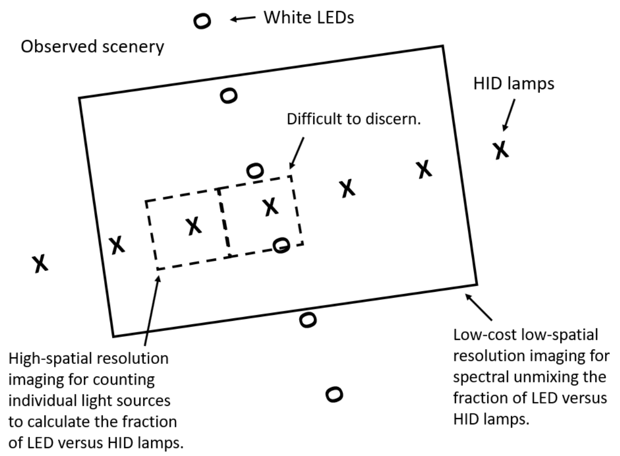


Figure 3: Illustration of a remote sensing platform measuring light pollution.

II. Motivation

Remote sensing technology (in combination with machine learning) is the paramount tool enabling scientists now to classify individual pixels of a high-resolution image, and discern a LED luminaire from conventional high-intensity discharge lamps. There has been previous research directed at identifying illumination sources [5] [6], which used 2-D imaging spectraphotometers boarded onto aerial remote sensing platforms. Both works successfully identified the type of public illumination source radiating light, by measuring the spectrum from afar. But, spectraphotometers are unsuited for low light level measurements and are marginally practical for CubeSat nano-satellite missions.

Red, green and blue (RGB) cameras are low-cost and practical imaging systems for nano-satellites, and they are able to discern white LEDs and HID light sources. Previous research showed promising results of discerning lighting types using a RGB camera mounted on a satellite: between a high-pressure sodium lamp and a white light-emitting diode [7]. This is possible since chromaticity coordinates of LEDs and HID lamps fall into different regions of the chromaticity diagram, as illustrated in Fig. 2. However, the point "Lamp type?" could have been obtained by measuring a mixture of a 6400 K LED and a high-pressure sodium lamp, or a mixture of a 4000 K LED and a high-pressure mercury lamp. They cannot be differentiated on the 2-D chromaticity diagram. Such a situation arises when neighbouring pixels are illuminated by a mixture of light radiated by two (or more) different luminaires (Fig. 3).

For this reason, one needs to employ more channels while considering the physical phenomena causing the emission spectra of the light sources (detailed in references [8] [9] [10] [11]). Glass arc tubes of HID lamps are filled with gas discharge plasma, in which an electric field excites atoms of sodium, mercury or metals present in the plasma. The atoms energized to higher atomic states spontaneously emit light in both the visible ($0.4 - 0.75$ µm) and the near-infrared spectrum ($0.75 - 2.5$ µm), depending on the plasma composition. In contrast, white LEDs spontaneously emit only in the visible spectrum by pumping blue light into a yellow phosphor layer, which converts a fraction of the blue light into red and green portions of the spectrum. Therefore, near-infrared channels provide orthogonal data measurements with respect to RGB channels, which is important for differentiating light sources.

Four channel: red, green, blue and near-infrared (RGB-IR) sensors provide an orthogonal channel (NIR) to standard RGB cameras for satellite payloads measuring light pollution. We investigated using a RGB-IR camera, but had difficulties with calibration of RGB-IR measurement data to construct a 3-D chromaticity diagram. We hence shifted our focus onto single pixel detectors. This dramatically lowers the spatial and spectral resolution, when compared to a camera. But, the advantage is a significantly simpler measurement system. We propose a multi detector system, for which spectral unmixing must be used to estimate the LED fraction versus the HID lamp fraction in a measured mixture of light.

Spectral unmixing is a well-established method in which a mixture of light, consisting of two or more distinctive spectra of illumination sources, is decomposed into its constituting component spectra and the fractions of the contributing spectra are determined. A detailed outlook on existing spectral unmixing methods is given in references [12] and [13].

In this work, we describe a spectral unmixing experiment for identification of lighting types, as measured by a spectraphotometer. The mixture spectra were formed with a high-intensity discharge (HID) lamp and a white light-emitting diode (LED); where-in for each mixture the LED/HID fractions were varied. The novelty of this work was to spectrally unmix the light into the constituent spectra. Using the *non-negative constrained least-squares* method we estimated the fractions of the constituent light sources with up to 93% accuracy. Furthermore, simulation results show that reducing the number of channels of the detector, from 3480 to only 7, did not reduce the quality of estimation.

III. THEORY

Let us represent the measurement setting with n light sources present at the surface of the Earth, where $s_i(\lambda)$ is the emission spectrum of the i-th light source (the power spectral density in $\mathrm{W/m^2}$). These light sources are measured using a spectraphotometer mounted on a satellite. The spectraphotometer is equipped with m pixels and the emission spectra from the light sources are all added at the spectraphotometer, namely, the light sources emit mutually independent beams of light. The measurement function $L\left(s_i(\lambda)\right)$ of the instrument converts photons from the spectrum $s_i(\lambda)$ into a vector of numbers during a finite integration time. Let the vector $\mathbf{s_i} = L\left(s_i(\lambda)\right) + \mathbf{e}_i$ with $m \times 1$ elements be the measurement of the i-th spectrum, where m is the number of channels. The vector $\mathbf{e}_i$ is an error, uncorrelated to the emitted spectrum, between the digitized data $\mathbf{s_i}$ and emitted spectrum $s_i(\lambda)$. We assume that the measurement function $L\left(s_i(\lambda)\right)$ of the spectraphotometer is a linear operator:

$$L\left(a_1 s_1(\lambda) + \cdots + a_n s_n(\lambda)\right) = \\ a_1 L\left(s_1(\lambda)\right) + \cdots + a_n L\left(s_n(\lambda)\right), \tag{1}$$

where $a_i \geq 0$ is a non-negative real number and $i = (1, \ldots, n)$.

Let the vector $\mathbf{y} = L\left(a_1 s_1(\lambda) + \cdots + a_n s_n(\lambda)\right) + \mathbf{e}_y$ with $m \times 1$ elements denote the digitized mixture spectrum and $\mathbf{e}_y$ any error uncorrelated with the mixture spectrum. Then, we can write (1) as:

$$\mathbf{y} = a_1 \mathbf{s_1} + \cdots + a_n \mathbf{s_n} + \mathbf{e}, \tag{2}$$

where the mutually uncorrelated errors $\mathbf{e}_i$ and $\mathbf{e}_y$ are substituted as $\mathbf{e} = \sum_i^n \mathbf{e}_i + \mathbf{e}_y$.

We form a spectral library matrix $\mathbf{S}$ containing measured spectra of reference light source types. Lamps used for public lighting are built by different manufacturers and each lamp has its distinct spectrum when compared to lamps of the same respective type. Therefore, the matrix $\mathbf{S}$ consist of n chosen representative spectra of n light source types with m pixels resulting in: $m \times n$ elements. As long as the vectors with which we formed $\mathbf{S}$ are highly correlated with the vectors $\mathbf{s_i}$, then (2) can be approximated as:

$$\mathbf{y} \approx \mathbf{S}\,\mathbf{a} + \mathbf{e}, \tag{3}$$

where $\mathbf{a} = [a_1, a_2, \ldots, a_n]$ is the vector containing the unknown fractions. Written out in matrix form it becomes:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{pmatrix} \approx \begin{pmatrix} s_{1,1} & \cdots & s_{1,n} \\ s_{2,1} & \cdots & s_{2,n} \\ \vdots & \ddots & \vdots \\ s_{m,1} & \cdots & s_{m,n} \end{pmatrix} \begin{pmatrix} a_1 \\ a_2 \\ \vdots \\ a_n \end{pmatrix} + \begin{pmatrix} e_1 \\ e_2 \\ \vdots \\ e_m \end{pmatrix}. \tag{4}$$

Our goal is to find the unknown fractions $\mathbf{a}$. Since $\mathbf{S}$ contains only estimates of what the vectors $\mathbf{s_i}$ might be, we can only estimate the fractions as $\hat{\mathbf{a}}$. The problem given in (3) is a least-squares problem which is solved by minimization of the error term $\mathbf{e^T e}$. The closed form solution is [14]:

$$\hat{\mathbf{a}} = \left(\mathbf{S^T}\,\mathbf{S}\right)^{-1}\,\mathbf{S^T}\,\mathbf{y}, \tag{5}$$

where $\mathbf{S^T}$ is the transposed matrix $\mathbf{S}$. Note that $\mathbf{S}$ is not a square matrix, except the case where the number of channels is equal to the number of light sources: $n = m$.

The first assumption of the least-squares model is that within a given scene, the mixture is formed by a finite number of distinct illumination sources with known spectra. The constituent spectra must hold relatively constant spectral properties $s_i(\lambda)$ during measurement. Any change in the digitized spectrum $\mathbf{s_i}$ would therefore appear as a change in the fractions a_i of the constituent spectra contained within the digitized mixture $\mathbf{y}_i$.

The second assumption is that spectra forming the spectral library matrix $\mathbf{S}$ are not collinear, which means that their mutual correlations are not high. For example, white LEDs of different correlated color temperature ratings of 4000 K and 6400 K emit a highly correlated spectrum (Fig. 1). Accurate estimation of the fractions, when we wish to unmix a mixture formed by a 4000 K and 6400 K white LED, depends on the spectral resolution m of the instrument.

There are situations in which solutions of (5) are not physical. For example, a negative value of a_i would imply a spectrum with negative intensity. To ensure realistic solutions, we must introduce a non-negativity and a sum-to-one constraint:

$$\sum_{i=1}^{n} a_i = 1, \tag{6}$$

$$a_i \geq 0, \quad (i = 1, \ldots, n). \tag{7}$$

Introducing the two constraints has a downside, as the problem now has no closed form solution. We refer the reader to a commonly used algorithm for the non-negative constrained least-squares solution without its deduction here [15, Chapter 23, p. 161.] (there are extensive derivations involved). The problem is formulated as a convex optimization problem which is solved numerically through an iterative algorithm.

In the following section we apply the method to laboratory measured high-resolution spectraphotometer data and affirmatively answer the question: whether it is possible to decompose a mixture of light into the constituent spectra.

IV. EXPERIMENT

In a laboratory setting, we measured mixtures of light formed by two independent light sources. The experiment, which was successful, was to estimate the fractions of the constituent spectra by decomposing the measured mixture of light using the non-negative constrained least-squares method.

The spectral measurements were done with a miniature USB spectraphotometer, Photon Control SPM-002-C (Fig. 4). The linear CCD array inside the instrument is a commercially available: Toshiba TCD-1304 (dimensions of 42 $\times$ 10 mm) with 3648 (8 $\times$ 200 $\mu\mathrm{m}$) pixels. Since the efficacy of the diffraction grating inside the instrument drops close to zero below 350 nm and above 1000 nm, the usable pixel indices start at 83 and end with 3563, resulting in 3480 effective pixels.

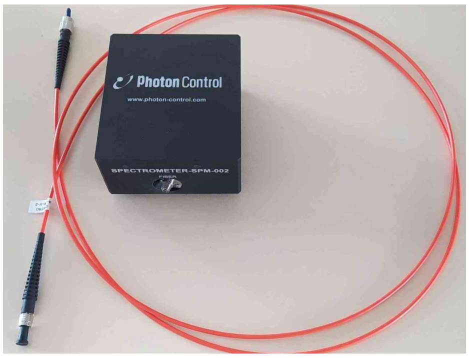


Figure 4: Photograph of the spectraphotometer and the $600\,\mu\mathrm{m}$ core diameter fiber cable.

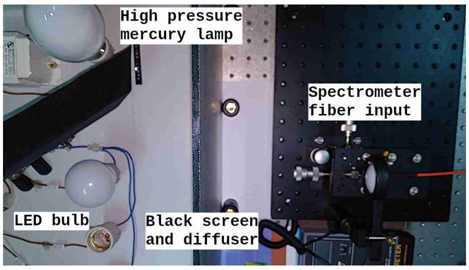


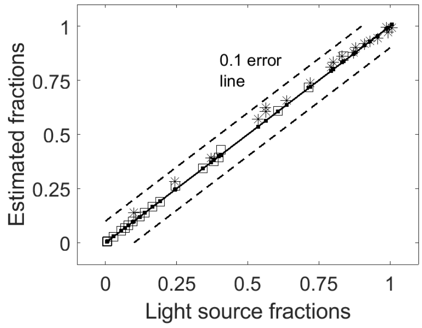
Figure 5: Photograph of the mixing experiment.

Three light sources were used in the experiment: a high-pressure sodium lamp [16], a high-pressure mercury lamp [17], and a white LED [18] with a correlated color temperature rating of 6400 K. We measured the individual spectra of all three light sources, as shown in Fig. 1, and using the measurement data, formed the spectral library matrix $\mathbf{S}$ with 3480×3 elements.

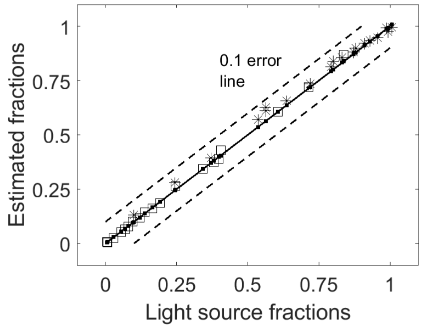
Next, we explain the experimental formation of the mixtures. Fig. 5 shows a photograph of the experiment in which two light source (a HID lamp and LED bulb) were positioned behind a diffuser which was covered by a black cardboard screen. A hole was made in the middle of the cardboard screen such that a small part of the light coupled into a spectraphotometer fiber entrance. The coupled light passing through was a mixture of light radiated by the two illumination sources where-in their fraction was proportional to their relative distance. By changing the relative positions of the two illumination sources we varied their fractions in the mixture. The exposure time of the spectraphotometer was fixed at 100 ms, and the number of averaged acquisitions was 50.

We proceeded with the experiment by positioning the lamps and measuring each individual spectrum. Due to the long time necessary for the HID lamps to reach a stable state for emission and the long cool-down time required before being started again, switching HID lamps 'on' and 'off' was not an option. Therefore, the HID lamp was powered during the entire experiment. During the short period of time required to measure the LED bulb spectrum, the light output of the HID lamp was blocked using a black cardboard box.

Next, we measured the mixture spectrum with both



(a) Using high-resolution data from 3480 channels.



(b) Using low-resolution data by simulating 2 channels.

Figure 6: Unmixing light into a HID and LED spectrum denoted by squares and stars, respectively.

light sources turned on. The energy of each spectrum was calculated by summing the intensities of all the pixels $E = \sum_{j=1}^{m} \mathbf{s_j}$. Intensities close to the noise floor were set to zero to mitigate noise. The mixture spectrum was normalized such that $\sum_{j=1}^{m} \mathbf{s_j} = 1$,

We decomposed the normalized mixture using the non-negative constrained least-squares method, resulting in estimated LED and HID fractions $\hat{a}_{LED}$ and $\hat{a}_{HID} = 1 - \hat{a}_{LED}$. Note that by normalizing the columns (spectra) of the spectral matrix $\mathbf{S}$ such that every column sums to one, the method does not depend on the absolute light intensity reaching the detector.

Finally, we compared the estimated fractions with the fraction of energy of each lamp in the spectrum. The absolute error in estimation was:

$$r_{HID} = |\hat{a}_{HID} - \frac{E_{HID}}{E_{MIX}}| \tag{8}$$

$$r_{LED} = |\hat{a}_{LED} - \frac{E_{LED}}{E_{MIX}}| \tag{9}$$

We repeated the experiment 19 times: 9 with the high-pressure sodium lamp and 10 with the high-pressure mercury lamp. Every time we varied the fractions. By decomposing the mixture spectra using the non-negative constrained least-squares method we estimated the LED (squares) and HID (stars) fractions in the mixture spectra. as shown in Fig. 6a. The dashed lines represent a 10% error in estimation, within which all of our estimates fit, as the maximum error in estimation was less than 7%. We confirmed that the method works.

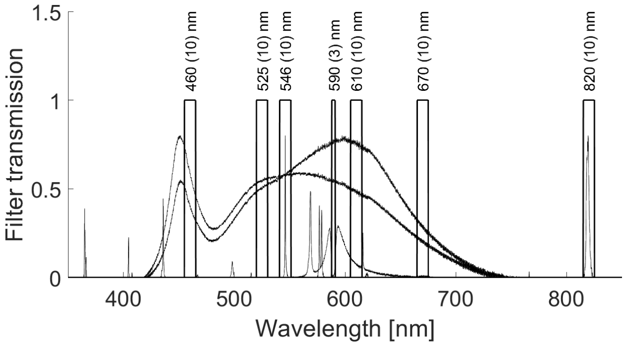


Figure 7: Transmission of chosen filters.

V. Proposed multidetector system

Next we discuss a simpler approach for unmixing. Rather than using a spectraphotometer with thousands of channels and limited responsivity, we explore the possibility of using the same algorithm on a limited number of narrow-band filtered detectors each tuned to a specific wavelength. Our reasons for using filtered detectors on a nano-satellite are: (i) larger sensitivity of detectors for measuring the faint nighttime light (ii) smaller size of optics required when compared to several-thousand-channel spectraphotometers. We designed a set of seven filters and simulated their effect on the high-resolution spectraphotometer data.

First, we considered all the emission lines of mercury and sodium, and selected two lines with the highest intensities: (i) Hg 546.1 nm. (ii) Na 818.4/819.5 nm. Second, we considered three of the most common emission lines present in metal-halide lamps: (iii) Na 589.0/589.6 nm, (iv) Li 610 nm, Na 615.4/616.1 nm, (v) Li 670 nm. Third, we considered the emission of white LEDs. We required the filters to capture as much of the LED spectrum while minimizing the light of all the other high-intensity discharge lamps, with metal-halide lamps presenting the largest problem. By visually comparing the spectra of the HID and LED light sources, we estimated that the two areas with least overlap are: (vi) between 455 nm and 465 nm, and (vii) between 520 nm and 530 nm. It is important to note that our selection of appropriate filters is a compromise and might not be the optimal set of filters for spectral unmixing.

The results for the filtered spectraphotometer data are shown in Fig. 6b. Applying the filters made a negligible change in results, when compared to using the high-resolution spectraphotometer data. From the results illustrated in Fig. 6b, we show that the large number of channels of the spectraphotometer can be reduced to a select few for the purpose of estimating the fractions of constituent light spectra which form a mixture.

VI. Summary

In this paper we have investigated the problem of light pollution by means of standard remote sensing instruments. This research demonstrates that imaging spectraphotometer data can be used to identify and spectrally unmix night lights based on their spectral signatures. The preliminary results have confirmed that unmixing is possible using narrow-band detectors having band-pass channels centered around spectral emission lines of commonly used public illumination sources.

VII. Acknowledgments

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References

[1] Noam Levine, et al. *"Remote sensing of night lights: A review and an outlook for the future."*, Remote Sensing of Environment, Volume 237, 2020, 111443, ISSN 0034-4257, doi:10.1016/j.rse.2019.111443.

[2] Falchia F., Cinzano P., C. D. Elvidge, D. M. Keith, Haimd A., *"Limiting the impact of light pollution on human health, environment and stellar visibility"*, Journal of Environmental Management, 2011. doi:10.1016/j.jenvman.2011.06.029

[3] Jurij Stare, www.lightpollutionmap.info. VIIRS 2020 data, Earth Observation Group, NOAA National Geophysical Data Center.

[4] C. D. Elvidge, et al. *"The Nightsat mission concept"*, International Journal of Remote Sensing, 28:12, 2645-2670, 2007, doi:10.1080/01431160600981525

[5] Barducci, Alessandro, et al. *"Hyperspectral remote sensing for light pollution monitoring."* Annals of Geophysics 49.1, 2006.

[6] F. A. Kruse and C. D. Elvidge, *"Characterizing urban light sources using imaging spectrometry."* 2011 Joint Urban Remote Sensing Event, Munich, 2011, pp. 149-152, doi: 10.1109/JURSE.2011.5764741.

[7] Q. Zheng, et al. *"A new source of multi-spectral high spatial resolution night-time light imagery—JL1-3B."* Remote sensing of environment 215 (2018): 300-312.

[8] de Groot, Josephus Johannes, and J. A. J. M. Van Vliet. *The High-pressure Sodium Lamp.* Macmillan International Higher Education, 1986.

[9] Waymouth, John F. *Electrical Discharge Lamps.* Cambridge, MA: MIT Press, 1971.

[10] Elenbaas, Willem, et al. *High Pressure Mercury Vapour Lamps and Their Applications.* NV Philips Gloeilampenfabrieken, 1965.

[11] D. A. Steigerwald et al., *"Illumination with solid state lighting technology."* IEEE Journal of Selected Topics in Quantum Electronics, vol. 8, no. 2, pp. 310-320, March-April 2002, doi: 10.1109/2944.999186.

[12] N. Keshava and J. F. Mustard, *"Spectral unmixing."* IEEE Signal Processing Magazine, vol. 19, no. 1, pp. 44-57, Jan. 2002, doi: 10.1109/79.974727.

[13] Carmen Quintano , Alfonso Fernández-Manso , Yosio E. Shimabukuro and Gabriel Pereira (2012) *"Spectral unmixing"*, International Journal of Remote Sensing, 33:17,5307-5340, DOI: 10.1080/01431161.2012.661095

[14] Seber, George AF, and Alan J. Lee. *Linear Regression Analysis.* Vol. 329. John Wiley & Sons, 2012.

[15] Lawson, Charles L., and Richard J. Hanson. *Solving Least Squares Problems.* Upper Saddle River, NJ: Prentice Hall. 1974.

[16] High-pressure sodium lamp: G.E. Lucalox™ LU 70/90/MO/D/E27

[17] High-pressure mercury lamp: Bellight 125BT 230B E27

[18] White light-emitting diode: VTAC A58 VT-210 SKU-230, 6400 K, 806 lm, CRI>80, $\theta = 200°$