

Development of a Hybrid Ultraviolet Imaging Algorithm for Optical Sensing Systems

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Hello, my name is Ron Cooper. I am currently a senior undergraduate student working on my Bachelor's in Electrical Engineering. I worked with a group of students and CANopenerLabs to help build the startup company "Dpower" as their electrical engineer.

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Abstract

This paper presents an undergraduate research experience in the design of a computer vision system by developing a novel combinational Ultraviolet (UV) image processing algorithm. The reflected-UV and UV fluorescence imaging methods are used in various scientific, industrial, and medical optical sensing systems, such as in digital forensics, industrial fault inspection, astronomy, dermatology (monitoring skin conditions), germicidal technology and in remote sensing. UV electromagnetic spectrum is defined as a wavelength range from 10 nm (below is x-ray wavelength) to 400 nm (above is visible to human eye). Digital imaging in this broad range of wavelengths requires multiple optical lenses with efficient UV transmission (pass filters). A system's cameras, optics, filtering and illumination must be carefully selected according to the UV ranges being imaged. Most of the system design depends on custom-built cameras with modified lenses and UV filters that are relatively expensive to operate, maintain and repair. In addition, UV imaging generated by a camera and lens combination are device dependent. For instance, in reflected-UV imaging, UV illumination reflects of an object and is recorded by a UV-sensitive camera. UV fluorescence imaging is based on the UV illumination that stimulates fluorescence at a longer wavelength than UV excitation source. The resulting fluorescence and image are typically in the visible band and can be captured by a color camera. These optical sensing system specific results require high-definition cameras with multispectral sensitivities. Thus, it is critical to provide an integrated and efficient approach to address the variability of UV based optical sensing systems.

The objective of the research is to develop a new adaptive UV image processing algorithm to transform our ability to combine reflected-UV and UV fluorescence techniques. The proposed algorithm uses a hyperspectral imaging technique to obtain the electromagnetic spectrum information from the pixels in the UV image to identify the wavelength range. The acquired data allowed the system to adapt to the spectral range and to provide hidden details in color images and efficiency in the UV imaging methods within the system.

Introduction

The Ultraviolet (UV) light accounts for 10% of the sun's total output but it is completely invisible to the human eye^{3,4}. There are three ranges of UV wavelengths, classified as: UVA, UVB, and UVC. The lowest wavelengths of UV light, which is UVC (100-280nm), are heavily obscured by the atmosphere. Optical imagers encompass imaging systems that operate in the visible, UVB (280 - 320nm), UVA (320 - 400nm), and Infrared segments of the EM spectrum. Full Spectrum digital cameras (sensors) can record reflected energy in all the light spectrums⁶. Figure 1 shows the optical imagers based on their electromagnetic (EM) spectrum, extending from the gamma-ray region to the radio region⁶.

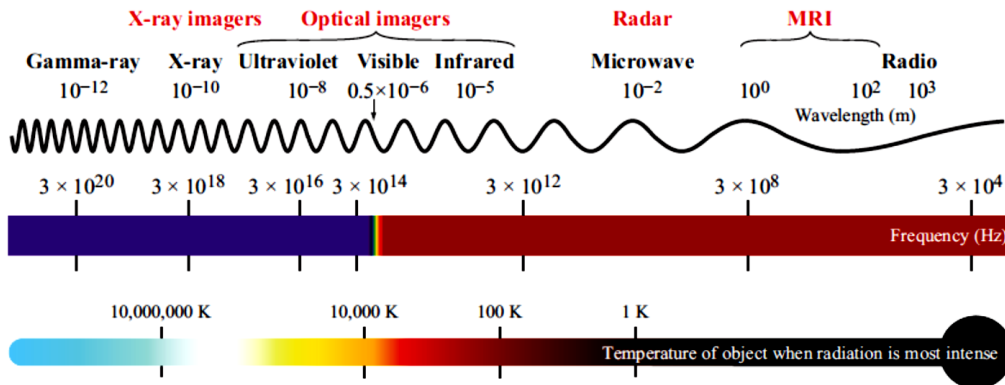


Figure 1. Electromagnetic spectrum⁶

UV light itself is not visible, but when a photon of ultraviolet radiation collides with an electron in an atom of a fluorescent material, it elevates the electron to a higher energy level. Figure 2 shows the energy levels of the EM spectrum. Subsequently, the excited electron relaxes to a lower level and emits light in the form of a lower-energy photon in the visible (blue) light region. The basic task of the fluorescence microscope is to use an excitation light to irradiate a prepared specimen and then to separate the much weaker radiating fluorescent light from the brighter excitation light. Thus, only the emission light reaches the eye or other detector, such as a full spectrum camera.

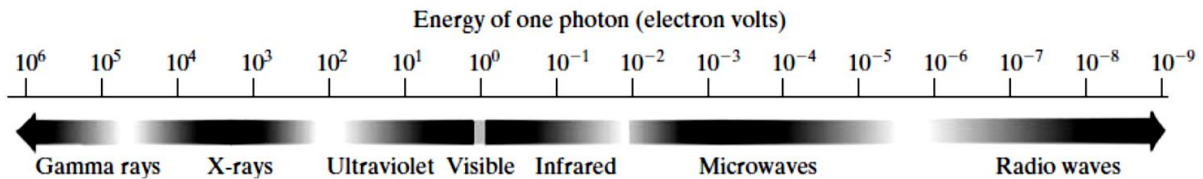


Figure 2. The electromagnetic spectrum arranged according to energy per photon⁵

The optical for reflected and fluorescent material sensing system specific results require high-definition cameras with multispectral sensitivities. Therefore, it is important to develop an integrated and efficient imaging technique to address the variability of UV based optical sensing systems.

Research Method

This section presents the overview of the proposed research to develop a new adaptive and combinational UV image processing algorithm. The MathWorks' MATLAB² software was used to develop the proposed imaging technique. The proposed algorithm uses a hyperspectral imaging technique to obtain the electromagnetic spectrum information from the pixels in the UV image to identify the wavelength range. Hyperspectral imaging measures the spatial and spectral characteristics of an object by imaging it at different wavelengths. The wavelength range extends beyond the visible spectrum and covers ultraviolet (UV) to long wave infrared (LWIR) wavelengths. A hyperspectral imaging sensor acquires several numbers of images with narrow and neighboring wavelengths within a specified spectral range. To visualize and understand the object being imaged, it is useful to represent the data as a 2-D image by using color schemes. The proposed algorithm represented the output of the hyperspectral information in UV, False-Color, and UV-Red-Green-Blue (UVRGB) composite formats. Figure 3 shows the hyperspectral analysis of an ultraviolet “Cardinal” image.

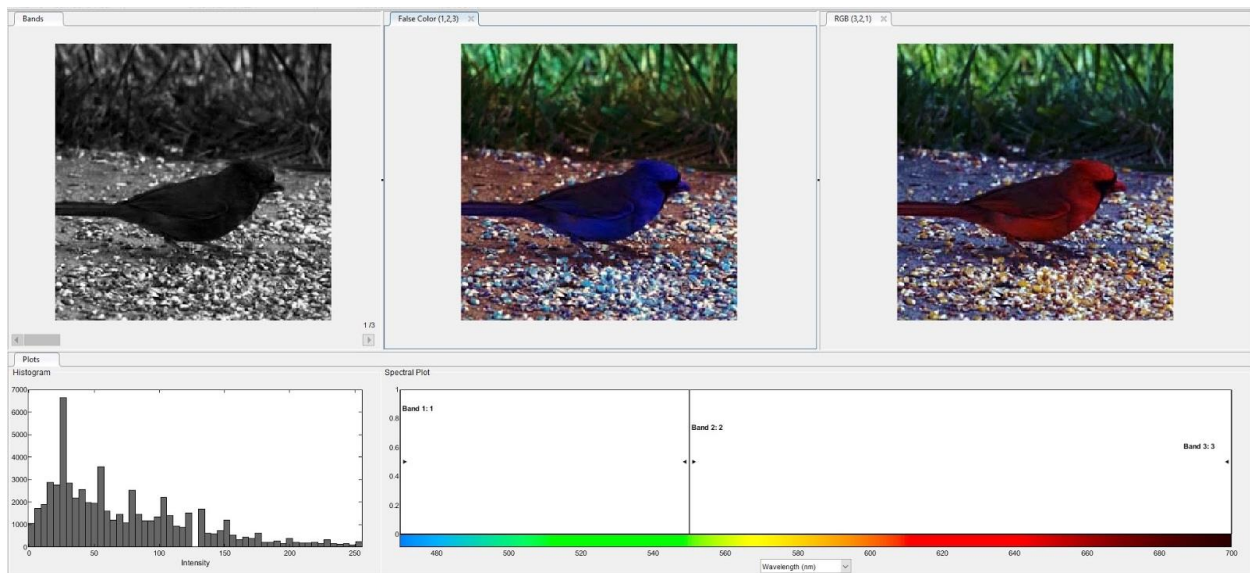


Figure 3. Hyperspectral analysis of an UV Image.

In Figure 3, three stages in identification of the wavelengths in the EM spectrum are displayed. First image in the figure above is the UV image. Second image is the False Color generated by using hyperspectral imaging technique to analyze the UV image to identify the wavelength range (380 nm, 550 nm, 680 nm respectively). The third image is the UVRGB composite that was generated based on the information gathered from the UV and False Color images to switch and replace the appropriate RGB layers for the output.

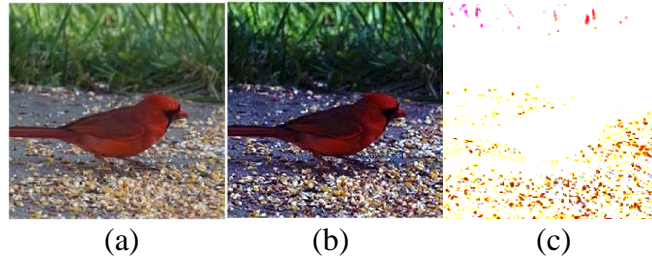


Figure 4: (a) Original RGB image, (b) UVRGB color composite image, (c) Difference between the original and UVRGB composite image

Figure 4 (c) shows the difference between the original RGB image and UVRGB composite to identify the details that are not visible in the original image. The “Cardinal” is reflecting lots of UV light that can be perceived to prevent the bird from overheating. On the other hand, the ground, some of the background green and seeds absorbed red and blue light. The difference illustrated the details of the UV lights reflected and fluorescent attributes in this example. Further needed testing of the proposed method on additional UV images can lead to various medical, agricultural, military applications, such as identification of microbial residue in an environment, in-depth vegetation analysis, satellite imagery, etc.

Conclusion – Lessons Learned

In this section, we present an assessment of the instructional and research (operational) impacts on the proposed research as lessons learned amid COVID-19 pandemic. This pandemic disrupted education worldwide, forcing schools and colleges to suspend in-person classes and casting doubt on a full resumption of regular instruction until a safe and effective vaccine became widely available⁸. Online teaching, a growing but supplemental segment of higher education market, and conducting research remotely became the only safe option available, testing the flexibility and resilience of students, faculty, and administrators alike. Engineering educators faced a particular challenge in providing a virtual substitute for the lab-based, hands-on experiences and teamwork that their discipline demands⁸.

The immediate challenges in the transition to remote research were to learn how to focus on the topic of investigation, to work in an online team environment and to manage time efficiently. In the Fall 2020 semester, the beginning of this project, redesigning the research objectives for remote operations introduced new challenges for the faculty mentor, such as establishing project online deliverables. For the student researcher, maintaining a full online credit load required greater time to learn remotely and stay focused and connected with research.

These above challenges were addressed by using weekly Zoom meetings, Microsoft Teams and Google Drive as daily interfaces to keep track of assigned tasks. The student research and faculty mentor met twice weekly via Zoom Video Conferencing. This allowed the team to stay focused on weekly tasks. Microsoft Teams provided a virtual open-door policy allowing quick connections to answer questions via chat online, transferring documents and scheduling meetings. The Google Drive was primarily used as a cloud storage for documents, such as publications, reports, presentations, schematics, etc., relevant to the research topic as a backup

and to be able to simultaneously edit the information. These applications enabled timely communications between the faculty and student and easily allowed the faculty to provide guidance and support in the research operations. Furthermore, the campus laboratory shutdowns presented a challenge for not having in-person access to high-performance computers to implement and test the algorithm on hardware. As an alternative to a virtual private network (VPN), the student researcher was provided with an individual MATLAB installed on a connected laptop by using the campus-wide license to implement and test the algorithm.

The authors strongly believe that the takeaway from this proposed undergraduate research is the importance of opportunities to develop not only basic skills, but also understanding, such that students learn to direct their own work. Mentors should allow students to see their uncertainty and provide support responsively but gradually transfer responsibility to the student. This fosters a sense of ownership, competency and belonging that allows students to grow further as they enter new research experiences^{1,9,10}.

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with pattern recognition applications to building innovative Internet of Things (IoT) and big data analytics frameworks to be implemented in real-time.